Exhibit 61

PLAINTIFFS' RESPONSE TO DEFENDANTS' MOTION TO EXCLUDE GENERAL CAUSATION TESTIMONY OF PLAINTIFFS' EXPERTS

EXHIBIT
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Murray
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Eating and Weight Disorders - Studies on Anorexia, Bulimia and Obesity (2024) 29:57
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RESEARCH

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Screen time, problematic screen use, and eating disorder symptoms among early adolescents: findings from the Adolescent Brain Cognitive Development (ABCD) Study

Jonathan Chu[1] · Kyle T. Ganson[2] · Alexander Testa[3] · Abubakr A. A. Al-shoaibi[1] · Dylan B. Jackson[4] · Rachel F. Rodgers[5,6] · Jinbo He[7] · Fiona C. Baker[8,9] · Jason M. Nagata[1]

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Level of evidence Level III: Evidence obtained from ...

PROSPECTIVE

ED

STUDIES

Keywords Eating disorders · Adolescent health · Screen time · Problematic screen use

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RESEARCH

Screen time, problematic screen use, and eating disorder symptoms among early adolescents: findings from the Adolescent Brain Cognitive Development (ABCD) Study

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Abstract

Purpose Emerging research evidence suggests positive relationships between higher screen time and eating disorders. However, few studies have examined the prospective associations between screen use and eating disorder symptoms in early adolescents and how problematic screen use may contribute to symptom development.

Methods We analyzed prospective cohort data from the Adolescent Brain Cognitive Development (ABCD) Study (N= 10,246, 2016–2020, ages 9–14). Logistic regression analyses were used to estimate the longitudinal associations between baseline self-reported screen time and eating disorder symptoms in year two. Logistic regression analyses were also used to estimate cross-sectional associations between problematic screen use in year two (either problematic social media or mobile phone use) and eating disorder symptoms in year two. Eating disorder symptoms based on the Kiddie Schedule for Affective Disorders and Schizophrenia (KSADS-5) included fear of weight gain, self-worth tied to weight, engaging in compensatory behaviors, binge eating, and distress with binge eating.

Results Each additional hour of total screen time and social media use was associated with higher odds of fear of weight gain, self-worth tied to weight, compensatory behaviors to prevent weight gain, binge eating, and distress with binge eating two years later (odds ratio [OR] 1.05–1.55). Both problematic social media and mobile phone use were associated with higher odds of all eating disorder symptoms (OR 1.26–1.82).

Conclusions Findings suggest greater total screen time, social media use, and problematic screen use are associated with more eating disorder symptoms in early adolescence. Clinicians should consider assessing for problem screen use and, when high, screen for disordered eating.

Level of evidence Level III: Evidence obtained from well-designed cohort or case–control analytic studies.

Keywords Eating disorders · Adolescent health · Screen time · Problematic screen use

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Introduction

Eating disorders are distressing and chronic disorders, linked to significant medical complications and reduced quality of life [1]. Examples of eating disorders include but are not limited to anorexia nervosa, bulimia nervosa, and binge-eating disorder, which are three of the most notable eating disorders among young people around the world [2]. The etiology of eating disorders is thought to be multifactorial. Studies have identified risk factors across biological, psychological, and sociocultural domains, such as genetic predisposition, elevated body mass index (BMI), comorbidity with other mental health disorders, socioeconomic status, and gender [3, 4]. Among these risk factors, a rising area of research is the relationship between screen use, the time spent using devices such as television, video game consoles, and mobile phones for various activities, and eating disorder risk [5, 6].

In recent years, the increasing popularity of social media has led to numerous studies describing the associations between social media use, body image, and eating concerns [7, 8]. However, the majority of these studies have occurred in mostly older female adolescents and young adults (approximately 15–29 years of age). While the focus on this age range is most likely related to the age of onset of clinical diagnoses, studies have shown that eating disorder symptoms may develop in early adolescence [9]. In addition, studies tend to focus on restrictive behaviors, excluding other symptoms of eating disorders such as compensatory behaviors (e.g., vomiting, excessive exercise) and binge eating and also eating disorder cognitions (e.g., feeling self-worth tied to weight, fear of weight gain, and distress with binge eating) that also make up DSM-5 criteria for eating disorder diagnoses [8, 10, 11]. The early adolescent population is known to also have increasing rates of screen use [12], and early symptom development may predispose individuals to long-term disordered eating [3, 13]. Furthermore, early adolescence is a key developmental period in which both the onset of puberty and increased social expectations impact mental health [14]. Therefore, it is imperative to further investigate these risk factors for eating disorders in younger populations to inform advancements in early identification and prevention.

Though the exact mechanisms through which screen time may influence the development of eating disorders is not yet fully understood, the Dual Pathways model describes how pressures to obtain socially constructed body ideals and subsequent body dissatisfaction increase the risk for negative eating disorder cognitions and disordered eating [15]. For example, increased exposure to idealized images of bodies on social media platforms (e.g., Facebook, Instagram, TikTok) may contribute to eating disorder symptoms in youth [16]. One cross-sectional study of 996 Australian adolescents with a mean age of 13 years linked increased social media usage with more disordered eating behaviors, suggesting that these influences may begin at younger ages [17]. However, the cross-sectional design of this study limited its generalizability regarding the directionality of the relationship and thus evidence for social media use as a risk factor for eating disorders. Therefore, longitudinal studies are needed to better understand media use as a potential risk factor for eating disorder symptoms in younger adolescents.

In addition to social media, it is also important to explore how other modalities of screen use, such as television, videos, video games, and texting factor into the potential development of eating disorder symptoms. One prior investigation found longitudinal associations between these screen time modalities and binge-eating disorder in early adolescents [6]. However, the eating outcomes assessed only included binge-eating disorder, and thus, individual symptoms characteristic of anorexia nervosa and bulimia nervosa, such as fearing weight gain, feeling self-worth tied to weight, and inappropriate compensatory behaviors/purging were overlooked. Increased screen time may influence emotional regulation in children and adolescents [5], and prior models have suggested strong associations between emotional dysregulation and eating disorders [18]. Thus, it is of importance to elucidate potential detrimental effects related to eating disorder risk.

Beyond the time spent using screens, further specific screen time behaviors and experiences should be investigated in relation to the risk of developing eating disorder symptoms. For example, problematic social media use, defined as the preoccupation with and compulsion to excessively engage in social media platforms [19], has been linked to deleterious outcomes in physical and mental health, including poorer mental health, sleep disturbances, and dietary problems [5]. Problematic mobile phone use shares similarities with problematic social media use and includes broader applications such as texting, apps, and video chatting. Studies have begun to examine the relationship between problematic screen use and negative eating habits and increased sedentary time [7, 20], suggesting that more problematic screen use is associated with higher body mass index [21, 22].

However, the associations between problematic screen use and eating disorder symptoms (e.g., body dissatisfaction) are less understood. In a large study of adolescents in Slovakia, eating disorder symptoms were associated with excessive internet use and potentially linked to poorer self-control and increased impulsivity [23]. As such, there may exist an overlap between the maladaptive behaviors and symptoms associated with eating disorders and the impulsivity related

to problematic screen use. Additional cross-sectional studies have also shown similar relationships between problematic screen use and eating disorders symptoms, but have primarily been limited to smaller samples and older populations [10, 24, 25]. As the literature has shown that both problematic screen use and eating disorder symptoms may begin in early adolescence [9, 26], further studies are needed to potentially inform early prevention strategies.

The current study aimed to determine the prospective associations between total screen time and social media use at baseline and eating disorder symptoms (e.g., fear of obesity, feeling self-worth is tied to weight, engaging in compensatory behaviors, binge eating, distress with binge eating) at two-year follow-up in a large, national sample of early adolescents. Given the availability of problematic screen use data at the 2-year follow-up, the study also sought to determine the cross-sectional associations between problematic screen use (e.g., problematic social media or mobile phone use) and eating disorder symptoms. To better understand the specific relationship between these screen measures and eating disorder symptoms, we adjusted for potential confounders based on known risk factors, including sociodemographic factors (age, race/ethnicity, household income, parent education status), BMI, anxiety, and impulsivity [3, 26, 27]. We hypothesized that higher total screen time and social media use would be prospectively associated with reporting eating disorder symptoms [6, 16, 17]. We also hypothesized that problematic screen use would be cross-sectionally associated with eating disorder symptoms [24, 25].

Methods

Study population

We analyzed prospective data from the Adolescent Brain Cognitive Development (ABCD) Study, a longitudinal study of brain development and health across adolescence in 11,875 children recruited from 21 sites around the U.S. The ABCD study implemented epidemiologically informed strategies to recruit a sample representative of U.S. diversity, largely through school systems and considering sociodemographic factors. Additional details are described elsewhere [28]. Data analyzed are from the ABCD 4.0 release for the baseline (2016–2018, 9–10 years old), year one (2017–2019) and year two (2018–2020) assessments. Participants with missing data for screen time and eating disorder symptoms were excluded ($N = 1,552$, 13.1%, characteristics of included and excluded participants may be found in Additional file 1: Table S1). For participants missing sociodemographic data at baseline, including race/ethnicity, sex, household income, parental education, and study site, we implemented Gaussian normal regression imputation in Stata to impute missing data. Centralized institutional review board (IRB) approval was obtained from the University of California, San Diego. Study sites obtained approval from their respective IRBs. Caregivers provided written informed consent and each child provided written assent. Data used in this study were obtained from the ABCD Study (https://abcdstudy.org), held in the NIMH Data Archive (NDA).

Exposures

Baseline total screen time and social media use

Total screen time and social media use were determined using the self-reported ABCD Youth Screen Time Survey. Participants answered questions about typical hours per day spent on six different screen time modalities (viewing/streaming television shows or movies, watching/streaming videos [e.g., YouTube], playing videogames, texting, video chatting [Skype, Facetime], and social media [e.g., Facebook, Instagram, Twitter]) separately for weekdays and weekend days, based on a previously validated measure [29, 30]. We calculated a weighted average of the participants' typical weekday and weekend screen time use, ((weekday average $\times$ 5) + (weekend average $\times$ 2))/7, to report a single typical hours per day measure for each modality [22, 31]. We reported the weighted average as a continuous variable after obtaining this screen time total for each modality utilized by participants. Total screen time was determined by summing the weight averages of all modalities.

Year-two problematic screen use

Problematic social media use

Starting in year two, the ABCD Study utilized the adolescent self-reported Social Media Addiction Questionnaire (SMAQ) to assess problematic social media. The six questions of the SMAQ were modeled after the Bergen Facebook Addiction Scale [32]. Examples of the questions included "I've tried to use my social media apps less but I can't" and "I've become stressed or upset if I am not allowed to use my social media apps." Likert-type scale responses ranged from 1 (never) to 6 (very often). Only participants who reported having at least one social media account were asked these items ($n = 5,587$).

Problematic mobile phone use

Starting in year two, a similar eight-question Mobile Phone Involvement Questionnaire (MPIQ) was used to assess problematic mobile phone use as reported by adolescents [33]. Examples of questions from the MPIQ included "I interrupt

whatever else I am doing when I am contacted on my phone" and "I lose track of how much I am using my phone." Likert-type scale responses ranged from 1 (strongly disagree) to 7 (strongly agree). This questionnaire has been previously used to assess smartphone dependence and digital multitasking during homework among US high school students [34]. Only participants who reported having mobile phones were asked these items ($n = 7{,}280$).

Outcome: year-two eating disorder symptoms

The ABCD Study utilized the Kiddie Schedule for Affective Disorders and Schizophrenia (KSADS-5), a widely used computerized tool for categorizing child and adolescent mental health concerns based on the DSM-5, for assessment of eating disorder symptoms at two-year follow-up [35, 36]. Participants completed all modules of the KSADS-5 to assess the frequency, duration, and characteristics of eating disorder symptoms. Examples of questions participants were asked included "Do you feel like your self-worth is tied to your weight?" and "Was there ever a time, for a month or longer, that you worried all the time about your weight or becoming fat?" Participants were also asked about behaviors such as compensatory behaviors to lose weight and binge eating. Compensatory behaviors included only eating foods with minimal calories, exercising a lot, throwing up, and taking water pills, laxatives, or diet pills. Those who responded yes to any of the behaviors were coded as engaging in compensatory behaviors to lose weight. Participants were asked about binge eating and whether they experienced distress with binge eating. Additional information regarding the KSADS-5 assessment of eating disorder symptoms used in this study may be found in Additional file 1: Table S2.

Confounders

We selected potential sociodemographic confounders based on previous literature and theory [3, 26, 27, 37]. Age (years), sex (female, male), race/ethnicity (White, Latino/Hispanic, Black, Asian, Native American, other), household income (grouped into two categories reflecting the US median household income: less than $75,000 and $75,000 or more), and highest parent education (high school or less vs. college or more) were based on parents' self-report at baseline. Participant BMI was recorded at baseline. Measures of impulsivity were obtained using the Behavioral Inhibition and Approach Systems scale in the ABCD Study, which assesses participant reward responsiveness, drive, and fun-seeking behavior [38, 39]. Anxiety symptoms at baseline were obtained from parent/caregiver responses to the Child Behavior Checklist (CBCL), a screening tool used to assess psychiatric symptoms and behavior problems in children aged 4–18 [28, 40]. Because participants were asked about eating disorder symptoms at the year two assessment but not asked at baseline, we included parent-reported baseline eating disorder symptoms of their child based on the caregiver KSADS-5 assessment as a confounder in longitudinal analyses. ABCD Study site was included as a confounder to adjust for potential regional variation.

Statistical analysis

Multiple logistic regression analyses were conducted using Stata 18.0 (StataCorp, College Station, TX) to (1) estimate prospective associations between screen time (exposure variable) and the presence of adolescent-reported eating disorder symptoms (fearing obesity, feeling self-worth tied to weight, engaging in compensatory behaviors to lose weight, and binge eating) at two-year follow-up, adjusting for confounders including parent-reported baseline eating disorder symptoms, and (2) estimate cross-sectional associations between problematic screen use and eating disorder symptoms, adjusting for confounders. Additionally, testing for interactions between eating disorder symptoms and sex was not statistically significant, and thus, we did not stratify by sex. Propensity weights developed by the ABCD Study were applied to yield estimates representative of the age, sex, and race/ethnicity distribution of US adolescents based on the American Community Survey from the US Census using the svyset and svy commands in Stata as described in the ABCD Study's guide for population-based analysis [38].

Results

Table 1 describes the sociodemographic characteristics of the 10,246 participants included. The sample was approximately matched by sex (48.6% female) and racially and ethnically diverse (45.6% non-White). At baseline, youth reported an average of 3.9 h of total screen time. At two-year follow-up, 1.4% reported fear of obesity, 1.6% felt their self-worth was tied to their weight, 0.7% engaged in compensatory behaviors to lose weight, 7.5% engaged in binge eating, and 2.9% had distress with binge eating.

Logistic regression analyses examining the prospective associations between baseline screen time and adolescent-reported eating disorder symptoms at two-year follow-up are shown in Table 2. In fully adjusted models, each additional hour of total screen time and social media use was prospectively associated with higher odds of fearing weight gain, feeling self-worth tied to weight, engaging in compensatory behaviors to prevent weight gain, binge eating, and distress with binge eating at two-year follow-up, with odds ratios ranging from 1.05 to 1.55.

Table 3 shows logistic regression analyses examining the cross-sectional associations between problematic screen use

Table 1 Sociodemographic, screen time, problematic screen use, and eating disorder symptoms among 10,246 Adolescent Brain Cognitive Development (ABCD) Study participants

Sociodemographic characteristics (baseline)	Mean (SD)/%
Age (years)	9.9 (0.6)
Sex, *n* (%)	
Female	48.6%
Male	51.4%
Race/ethnicity (%)	
White	54.4%
Latino/Hispanic	19.7%
Black	16.0%
Asian	5.4%
Native American	3.2%
Other	1.4%
Household income (%)	
Less than $75,000	45.0%
$75,000 and greater	55.0%
Parent with college education or more (%)	81.2%
Screen time measures	
Total screen time at baseline (hours)	3.9 (3.1)
Total screen time at year one of follow-up (hours)	4.7 (3.6)
Total screen time at year two of follow-up (hours)	6.1 (5.9)
Social media (hours)	0.1 (0.4)
Problematic screen use measures	
Social media addiction questionnaire score[a]	1.9 (0.9)
Mobile phone involvement questionnaire score[b]	3.1 (1.1)
Eating disorder symptoms	
Fear of obesity	1.4%
Self-worth tied to weight	1.6%
Inappropriate compensatory behaviors to prevent weight gain	0.7%
Binge eating	7.5%
Distress with binge eating	2.9%
BMI (kg/m^2)	18.9 (4.2)
BMI percentile	61.6 (30.8)
Weight (kg)	28.0 (13.5)
Weight percentile	61.8 (29.7)
Anxiety symptoms (t-score)	53.7 (6.3)
BAS reward responsiveness sum score	2.2 (0.6)

Propensity weights were applied to yield representative estimates based on the American Community Survey from the US Census. SD = standard deviation

[a]Asked among a subset who reported social media use ($n = 5{,}587$)

[b]Asked among a subset who reported mobile phone use ($n = 7{,}280$)

(social media use or mobile phone use) and eating disorder symptoms at two-year follow-up. Both problematic social media use and problematic mobile phone use were associated with all eating disorder symptoms in fully adjusted models with odds ratios ranging from 1.26 to 1.82.

Discussion

In this population-based, demographically diverse cohort of early adolescents in the US, we found that greater

Table 2 Associations between baseline total screen time and eating disorder symptoms at two-year follow-up in the Adolescent Brain Cognitive Development Study

Eating disorder symptom	Total screen time[a]		Social media use[a]	
	OR (95% CI)	p	OR (95% CI)	p
Fear of obesity	**1.12 (1.08–1.17)**	**<0.001**	**1.55 (1.21–1.98)**	**0.001**
Self-worth tied to weight	**1.10 (1.06–1.15)**	**<0.001**	**1.30 (1.03–1.63)**	**0.025**
Inappropriate compensatory behaviors to prevent weight gain	**1.06 (1.03–1.09)**	**<0.001**	**1.18 (1.01–1.40)**	**0.039**
Binge eating	**1.08 (1.05–1.11)**	**<0.001**	**1.28 (1.10–1.49)**	**0.002**
Distress with binge eating	**1.05 (1.01–1.09)**	**0.011**	**1.31 (1.06–1.61)**	**0.012**

Bold indicates $p < 0.05$

[a]Covariates: race/ethnicity, sex, household income, parent education, site, baseline parent-reported eating disorder symptom, baseline BMI percentile, baseline anxiety symptoms, and baseline BAS reward responsiveness

Table 3 Cross-sectional associations between problem screen time use and eating disorder symptoms in the Adolescent Brain Cognitive Development Study

Eating disorder symptom	Problematic social media use[a]		Problematic mobile phone use[a]	
	$n = 5{,}587$[b]		$n = 7{,}280$[b]	
	OR (95% CI)	p	OR (95% CI)	p
Fear of obesity	**1.38 (1.11–1.71)**	**0.004**	**1.43 (1.18–1.72)**	**<0.001**
Self-worth tied to weight	**1.75 (1.45–2.10)**	**<0.001**	**1.51 (1.27–1.79)**	**<0.001**
Inappropriate compensatory behaviors to prevent weight gain	**1.43 (1.28–1.60)**	**<0.001**	**1.26 (1.15–1.39)**	**<0.001**
Binge eating	**1.63 (1.48–1.81)**	**<0.001**	**1.66 (1.51–1.81)**	**<0.001**
Distress with binge eating	**1.79 (1.54–2.08)**	**<0.001**	**1.82 (1.57–2.12)**	**<0.001**

Bold indicates $p < 0.05$

[a]Covariates: race/ethnicity, sex, household income, parent education, site, baseline BMI percentile, baseline anxiety symptoms, and baseline BAS reward responsiveness

[b]Assessments for problematic social media and mobile phone use were only performed on participants who responded "yes" to having a social media account or mobile phone, respectively

screen time and social media use were prospectively associated with eating disorder symptoms at two-year follow-up. We also revealed cross-sectional associations between problematic screen use and eating disorder symptoms. In particular, problematic social media use was most strongly associated with feeling self-worth tied to weight, and problematic mobile phone use was most associated with binge eating.

Our findings regarding the relationship between screen time, social media use, and eating disorder symptoms are consistent with prior studies [8, 10, 17]. While this relationship has been previously examined, longitudinal studies are scarce, particularly in younger adolescents, making this an important extension of previous work. Furthermore, as screen time and media use patterns rapidly evolve over time, continued studies are necessary to best capture their potential influence on youth growing up in different periods. Thus, we add to the literature by (1) using a large, national prospective cohort design; (2) focusing on early adolescence, an important period for the development of screen use and eating disorder symptoms; and (3) examining the associations between problematic screen use and eating disorder symptoms.

Of note, social media use only made up a small portion of total screen time in this population of early adolescents and had significant associations particularly with fear of weight gain. Through social media, youth may gain exposure to unrealistic beauty standards that could precipitate low self-esteem, leading to concerns regarding weight and body image [10, 17, 41]. The other forms of screen time that were not focused on in this study and which youth appear to be engaging with at higher amounts (e.g., television, videos, video games, texting) may also expose youth to similar content. Television shows and advertisements frequently depict and glamorize thinness in women and muscularity in men [42]. Influencers across various platforms, such as Instagram, YouTube, or TikTok have been shown to motivate and positively impact people's exercise goals [43]; however, they often portray a "fit" ideal that may similarly lead to body dissatisfaction [20]. Future studies may seek to identify the relationships between

specific screen time modalities and content that place youth at the greatest risk for developing eating disorder symptoms.

The relationship between problematic screen use and disordered eating is less well described in the literature, with existing studies primarily focusing on older adolescents, college students, and young adults [23, 25, 44]. In contrast to benign use, problematic screen use involves dependence and inability to remove oneself from screens, resulting in functional impairment in daily life. Prior studies have shown that problematic screen use and internet addiction may contribute to the development of poor eating habits [45]. For example, individuals may become so engrossed in their screen use that they unwittingly engage in disordered eating behaviors such as skipping meals to spend more time on their devices or binging due to a lack of awareness around how much they have eaten. Some preliminary studies have shown that mindful and intuitive eating practices, approaches to healthy eating that focus on non-judgmental observations of sensations and cognitions during meals, may reduce disordered eating behaviors [46]. As such, it may be possible that the decreased engagement during meals because of problematic screen use can predispose individuals to develop eating habits that then transform into disordered eating.

In our study, the association with the largest odds ratio was between problematic social media use and feeling self-worth tied to weight. Models describing the etiology of eating disorders often include environmental factors such as social pressure regarding physical appearance [47]. Social media has erupted in the last decade, resulting in increased connectedness to peers [48]; however, increased exposure may result in negative cognitions around body dissatisfaction, fearing obesity, and greater emphasis on body image due to social comparisons with content that embodies thinness ideals [10, 17]. Those who engage in problematic social media use are potentially more prone to constantly comparing themselves to other social media users at greater frequencies, which has been shown to have associations with body dissatisfaction and drive for thinness [16]. Consequently, it is possible that constant social media use can make adolescents more vulnerable to these body ideals and feelings of self-worth tied to their weight and body image.

In addition to these negative body image cognitions, we also found that problematic screen use was associated with binge eating and compensatory behaviors to prevent weight gain. Binge eating involves the overconsumption of food in a short period coupled with a loss of control during episodes. In a prior study, we showed that total screen time was longitudinally associated with binge-eating disorder. However, that study did not examine problematic screen use. Combined with purging, which are compensatory behaviors such as vomiting or excessive exercise to prevent weight gain, binge eating also contributes to bulimia nervosa as well as the binge–purge subtype of anorexia nervosa [49]. Theoretical frameworks attempting to explain the etiologies of these disorders have discussed the potential role of impulsivity [50, 51]. The seemingly impulsive nature of binge eating and purging may share similarities with characteristics of addiction and problematic screen use. Poor inhibitory control in impulsivity has well-established links to addictive behaviors [52]. Impulsivity generally refers to taking action or engaging in behaviors without consideration of consequences. High levels of impulsivity are thought to increase the risk of binge–purge episodes and have been demonstrated in longitudinal studies of adults as well as cross-sectional studies of adolescents [51, 53, 54]. Problematic usage and overconsumption of either social media or mobile phones may reflect the similar loss of control and overconsumption exhibited through binge-eating behaviors, which is consistent with our longitudinal findings between total screen time and eating disorder symptoms. Furthermore, children may be prone to overeating in the absence of hunger while distracted in front of screens. Finally, researchers posit that media and advertising content that youth may become exposed to can reflect unattainable body ideals and exacerbate binge eating [41], and adolescents who hold negative feelings towards their own body image are more likely to binge eat [55].

Our study includes notable limitations. Although we adjusted for several potential confounders, including parent-reported baseline eating disorder symptoms, the possibility of residual confounding due to other factors exists. Though the prospective study design for analyses between screen time and eating disorder symptoms improves on prior cross-sectional evidence, we cannot establish causality given the observational nature of the study. As the prevalence of eating disorder symptoms and the diagnoses of eating disorders increase as youth enter later adolescence, additional studies following the ABCD cohort will be an important area of future research. Furthermore, in this study eating disorder symptoms were assessed by parents at baseline and then adolescents at two-year follow-up since participants themselves were not screened for symptoms at baseline. Prior studies have demonstrated parents may provide lower estimates of eating disorder symptoms [56]; however, we acknowledge that generally, there exists discordance between youth–parent reporting of eating disorder pathology that future research may consider evaluating further [56]. Additionally, in this study eating disorder symptoms were analyzed categorically rather than dimensionally, which may not capture the relationship between screen use and the spectrum of symptom severity. It is important to note that the effect sizes of the associations between screen time and eating disorder symptoms were relatively small. However, they are reported for each additional hour, and thus, greater exposure may result in higher odds of developing symptoms. Despite the large sample

size, participants in the study represent adolescents only within the US, which limits generalizability as both screen time and eating disorder patterns can vary in different regions globally [57, 58]. Because problematic screen use measures were not asked at the initial assessment of the ABCD Study, we were unable to determine the prospective associations between problematic screen use and eating disorder symptoms, though this may be another area of future research. Finally, all measures, including evaluations of screen time and eating disorder symptoms, were based on self-reported responses to survey questions and may be subject to reporting bias.

Given the ubiquitous nature of screen and media use in society and the mounting evidence for risks associated with their use, it is imperative to understand their potential downstream effects on youth. Especially with recent rises in both screen use and eating disorders [12, 59], future research should continue to examine their relationship in adolescent populations. Parent education regarding digital media literacy, which has been shown in some studies to decrease screen time in children, can potentially include guidance on body image concerns. The American Academy of Pediatrics encourages the development of Family Media Use Plans, which can include discussions surrounding problematic screen use and disordered eating concerns with children. Clinicians are encouraged to regularly assess screen time in youth, given the accumulating support for its association with a range of poor mental health outcomes. Moreover, clinicians should consider screening for disordered eating in youth who report high or problematic screen use, given the benefits of early identification for prognosis.

Strength and limits

Strengths of the study include the analysis of a large, diverse prospective cohort of early adolescents in the US. Limitations include the use of self-reported measures which could be subject to reporting bias, the lack of problematic screen use measures at baseline, and the possibility of residual confounding.

What is already known on the subject?

Emerging research evidence suggests positive relationships between higher screen time and eating disorders. However, few studies have examined the prospective associations between screen use and eating disorder symptoms in early adolescents and how problematic screen use may contribute to developing eating disorder symptoms.

What does this study add?

Findings suggest greater total screen time, social media use, and problematic screen use are associated with more eating disorder symptoms in early adolescence. Clinicians should consider assessing for problem screen use and, when high, screen for disordered eating.

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Author contributions JC conducted the analysis, drafted the manuscript, and edited the manuscript. KG, AT, DJ, RR, JH and FB provided critical revision of the manuscript. JN conceptualized the study, provided critical revision of the manuscript, and provided supervision. All authors approve the final manuscript.

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Availability of data and materials Data used in the preparation of this article were obtained from the ABCD Study (https://abcdstudy.org), held in the NIMH Data Archive (NDA).

Declarations

Ethics approval and consent to participate Centralized institutional review board (IRB) approval was obtained from the University of California, San Diego. Study sites obtained approval from their respective IRBs, caregivers provided written informed consent, and each child provided written assent.

Informed consent Not applicable.

Competing interests The authors declare no competing interests.

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Contemporary Screen Time Modalities among Children 9–10 years old and Binge-Eating Disorder at One-Year Follow-Up: A Prospective Cohort Study

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Abstract

Objective: To determine the prospective associations between contemporary screen time modalities in a nationally representative cohort of 9–11-year-old children and binge-eating disorder at one-year follow-up.

Method: We analyzed prospective cohort data from the Adolescent Brain Cognitive Development (ABCD) Study (N=11,025). Logistic regression analyses were conducted to estimate associations between baseline child-reported screen time (exposure) and parent-reported binge-eating disorder based on the Kiddie Schedule for Affective Disorders and Schizophrenia (KSADS-5, outcome) at one-year follow-up, adjusting for race/ethnicity, sex, household income, parent education, BMI percentile, site, and baseline binge-eating disorder.

Results: Each additional hour of total screen time per day was prospectively associated with 1.11 higher odds of binge-eating disorder at 1-year follow-up (95% CI 1.05–1.18) after adjusting for covariates. In particular, each additional hour of social networking (aOR 1.62, 95% CI 1.18–2.22), texting (aOR 1.40, 95% CI 1.08–1.82), and watching/streaming television shows/movies (aOR 1.39, 95% CI 1.14–1.69) was significantly associated with binge-eating disorder.

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Conflicts of interest statement: The authors have no conflict to declare.

Discussion: Clinicians should assess screen time usage and binge eating in children and adolescents and advise parents about the potential risks associated with excessive screen time.

Keywords

Screen time; television; social media; smart phone; binge eating; binge-eating disorder; eating disorder; disordered eating; pediatrics; adolescents

Introduction

The advancement and accessibility of technology has led to the rapid increase in children and adolescents using screens to interact with the world (Hill et al., 2016). As time spent in front of screens has risen, so have concerns regarding the effects of excessive screen time on young people's wellbeing (Hill et al., 2016; Viner et al., 2019). Recent research has linked excessive screen time with adverse effects on children's health, including depression, anxiety, inattention, poor sleep, and physical inactivity (Lissak, 2018; Viner et al., 2019), although it is increasingly apparent that effects of screen time are nuanced, depending on various factors, such as level of engagement and interaction (Orben & Przybylski, 2019; Przybylski et al., 2020).

One particular area of interest is the relationship between excessive screen time and binge eating. Prior studies have demonstrated links between screen time and snacking (Fiechtner et al., 2018; Kim et al., 2020); however, fewer studies have specifically addressed the relationship between screen time and binge eating. Screen time could be linked to binge eating through overeating in the absence of hunger during passive (as opposed to interactive) screen time (Fiechtner et al., 2018; Kim et al., 2020), binge-watching behaviors (Flayelle et al., 2019; Vizcaino et al., 2020), and negative body image (Dakanalis et al., 2015). Furthermore, while research in this area has progressed from the initial focus on television-watching, screen interactions have continued to diversify rapidly since the advent of video games, texting, and social media, and require further continual investigation to differentiate potential effects.

Moreover, the majority of current literature focuses on older adolescents or adults (Burmeister & Carels, 2014; Smith et al., 2013). However, children's screen time usage increases at the greatest rate in early adolescence (Smink et al., 2012; Twenge & Campbell, 2018). Some studies have examined the cross-sectional association between screen time and binge eating in children and adults (Burmeister & Carels, 2014; Fiechtner et al., 2018; Vizcaino et al., 2020), but few have used longitudinal study designs or focused on younger adolescents. One study analyzing clinical samples of children and adolescents for weight loss treatment found a subgroup (n=15) where eating alone, in some cases while watching television, was associated with binge eating (Tanofsky-Kraff et al., 2007). Another population-based study of adolescents in Minnesota did not find an association between television viewing and binge eating (Neumark-Sztainer et al., 2007). However, there is a paucity of data using large, diverse, longitudinal samples examining the association between specific types of screen time and binge-eating disorder in early adolescents using

the Diagnostic and Statistical Manual, 5th Edition (DSM-5) criteria (American Psychiatric Association, 2013).

The objective of this study was to determine the prospective associations between screen time in a population-based, demographically diverse cohort of 9–10-year-old children in the U.S and binge-eating disorder at one-year follow-up. In addition, we sought to identify the specific types of screen time (television, videos, video games, texting, video chat, and social networking) that are associated with binge eating. We hypothesized that excessive screen time, particularly passive forms (television, videos) and those that may exacerbate a negative body image (social networking), would be prospectively associated with binge-eating disorder at one-year follow-up.

2. Methods

2.1 Study Population

We analyzed prospective cohort data from the Adolescent Brain Cognitive Development (ABCD) Study, a longitudinal study of brain development and health across adolescence consisting of 11,875 children recruited from 21 sites around the U.S. (See (Barch et al., 2018) for descriptions of study sample, recruitment, procedures, and measures). Data analyzed here are from the ABCD 3.0 release for the baseline (2016–2018, ages 9–10 years) and one-year follow-up (2017–2019, ages 10–11 years) assessments. Participants with missing data for baseline screen time (N=63) or binge-eating disorder at one-year follow-up (N=793) were excluded, leaving a total of 11,025 participants in the cohort. For participants with missing covariate data (N=1,016), Gaussian normal regression imputation was used to impute missing covariate data. Centralized institutional review board (IRB) approval was obtained from the University of California, San Diego. Study sites obtained approval from their local IRBs. Caregivers provided written informed consent and each child provided written assent.

2.2 Measures

Exposures: Screen Time—Screen time was determined using the self-reported ABCD Youth Screen Time Survey. Participants answered questions about typical hours per day spent on six different screen modalities (viewing/streaming television shows or movies, watching/streaming videos [e.g. YouTube], playing videogames, texting, video chatting [e.g. Skype, Facetime], and social networking [e.g. Facebook, Instagram, Twitter]) separately for weekdays and weekend days, based on a previously validated measure (Bagot et al., 2018; Gray et al., 2019; Paulus et al., 2019; Sharif et al., 2010). We calculated a weighted average calculation of the participants' typical weekday and weekend screen time use (((weekday average × 5) + (weekend average × 2))/7) to report a single typical hours per day measure (Guerrero et al., 2019). After obtaining this screen time total for each type of media utilized by the participants, we reported the weighted average as a continuous variable.

Outcome: Binge-Eating Disorder—The ABCD Study utilized the Kiddie Schedule for Affective Disorders and Schizophrenia (KSADS-5), a computerized tool for categorizing child and adolescent mental health concerns based on the DSM-5 (American Psychiatric

Association, 2013), for assessment of current binge-eating disorder at baseline and one-year follow-up (Townsend et al., 2020). Parents/caregivers completed the binge-eating disorder modules of the KSADS-5 (assessing frequency, duration, characteristics, and associated distress of their child's binge eating) on behalf of their child given evidence that parents are particularly important reporters for these behaviors in this age range (Barch et al., 2018) and young children may have less insight regarding their eating behaviors (Braet et al., 2007). Using the KSADS-5 computerized scoring system, responses to the interview questions from parents were extrapolated into the diagnosis of current binge-eating disorder from reported symptoms corresponding to the DSM-5 (American Psychiatric Association, 2013).

Covariates: Sociodemographic covariates were selected based on previous literature and theory as being potential confounders for the association between screen time and binge-eating disorder (Fiechtner et al., 2018; Neumark-Sztainer et al., 2007; Tanofsky-Kraff et al., 2007). Age (years), sex assigned at birth (female, male (including three intersex-male participants)), race/ethnicity (White, Latino/Hispanic, Black, Asian, Native American, other), past year household income (dollars, six categories), and highest parent education (high school or less vs. college or more) were based on parents' self-report. Body mass index (BMI) was based on measured height and weight (BMI = weight/height^2) and converted into sex and age-specific percentiles in accordance with CDC growth curves (Centers for Disease Control and Prevention, 2019).

Statistical Analysis—Data analysis was performed in 2020 using Stata 15.1 (StataCorp, College Station, TX). Unadjusted logistic regression analyses estimated the association between baseline screen time (total and each type of screen time independently) and binge-eating disorder at one-year follow-up. Multiple logistic regression analyses were conducted to estimate the association between baseline screen time (total and each type of screen time independently; exposure) and binge-eating disorder at one-year follow-up (outcome), adjusting for sex, race/ethnicity, household income, parent education, site, and baseline binge-eating disorder. Some children within the sample were twins or siblings. Sensitivity analyses were conducted including only one sibling per family and findings did not differ; therefore, we present results from the full sample. We tested for effect modification by sex and present sex-stratified results where sex significantly modifies the association between screen time and binge-eating disorder ($p<0.05$). Propensity weights were applied to yield nationally representative estimates based on the American Community Survey from the US Census (Heeringa & Berglund, 2020).

Results

Table 1 describes sociodemographic characteristics of the 11,025 participants included. The sample was approximately matched by sex (48.8% female) and was racially and ethnically diverse (47.6% non-White). On average, at baseline, children reported 4.0±3.2 hours (mean±SD) of screen time per day, with the most time spent watching/streaming television shows/movies (1.3±1.3 hours), playing video games (1.1±1.1 hours), and watching/streaming videos (1.1±1.2 hours). At one-year follow-up, 1.1% of participants met criteria for binge-eating disorder.

Table 2 shows logistic regression analyses examining the prospective associations between baseline screen time and binge-eating disorder at one-year follow-up. In unadjusted models, all forms of screen time were associated with binge-eating disorder at one-year follow-up. In models adjusting for covariates, each additional hour of total screen time per week at baseline was prospectively associated with 1.11 higher odds of binge-eating disorder at one-year follow-up (95% confidence interval [CI] 1.05–1.18). The screen time types that were most strongly associated with binge-eating disorder in fully-adjusted models were social networking, texting, and television/movie viewing. There was no evidence of effect modification by sex for any of the screen time exposures (all $p>0.05$) except for video games ($p=0.013$). Each additional hour of video games at baseline was prospectively associated with higher odds of binge-eating disorder in females (AOR 1.54, 95% CI 1.11–2.14, $p=0.010$) but not males (AOR 0.92, 95% CI 0.73–1.16, $p=0.486$).

Discussion

In a population-based, demographically diverse cohort of 9–10-year-old children in the U.S., we found that greater screen time was prospectively associated with binge-eating disorder at one-year follow-up. In particular, more time spent social networking, texting, and watching/streaming television were most strongly associated with incident binge-eating disorder.

Our findings confirm those of mostly cross-sectional studies (Burmeister & Carels, 2014; Fiechtner et al., 2018; Vizcaino et al., 2020) in older adolescents or adults (Burmeister & Carels, 2014; Smith et al., 2013) examining the relationship between screen time and binge eating. We add to the prior literature on screen time and binge eating by: 1) using a nationally representative prospective cohort design, 2) focusing on an important developmental period for screen time and binge eating (children 9–10 years old followed for one year), and 3) assessing DSM-5 binge-eating disorder as an outcome. The estimates of daily screen time (four hours per day, on average) and binge-eating disorder (0.7%–1.1%) in the ABCD Study were consistent with those from other epidemiological studies with overlapping age ranges (Fiechtner et al., 2018; Marzilli et al., 2018).

As technology platforms consistently evolve and diversify, the need to study new specific screen time mediums now accessible to children and their impacts on binge eating is important. We find that greater amounts of time spent on social networking, texting, and watching television shows/movies are associated with binge-eating disorder. This finding is similar to prior studies that identified television and social networking as associated with triggering binge-eating episodes (Burmeister & Carels, 2014; Smith et al., 2013; Tanofsky-Kraff et al., 2007). We add to this literature by showing that more time spent texting, a relatively new form of screen time for children, is a potential risk factor for subsequent binge-eating disorder, as well. Of note, we did not find significant associations between video chat or video games (except in females) and binge-eating disorder. These forms of screen time may be more interactive and, thus, children may be less prone to binge eating during these more interactive pursuits (Kim et al., 2020; Yland et al., 2015).

Several mechanisms may help to explain the prospective association between screen time and binge eating, including overeating in the absence of hunger, binge-watching behaviors,

and negative body image. First, children may be more prone to overeating in the absence of hunger while distracted in front of screens (Fiechtner et al., 2018; Kim et al., 2020). Second, binge-watching behaviors may lead to overconsumption and a loss of control, similar to binge-eating behaviors (Flayelle et al., 2019; Vizcaino et al., 2020). Third, adolescents who hold negative feelings towards their own body image are more likely to binge eat, and researchers posit that media or advertising content reflecting an unattainable body ideal may exacerbate binge eating (Dakanalis et al., 2015).

Limitations of the study should be noted. Although we adjusted for several potential confounders, including baseline levels of binge eating and BMI percentile, there is the possibility of residual confounding. There may be a bidirectional relationship between screen time and binge-eating disorder, which should be explored in future research. While the prospective study design improves on prior cross-sectional evidence, given the observational study design, we cannot definitively establish causality. The screen time measures were based on self-report, which could be subject to reporting bias. Future studies could use automated measurements of device use to assess screen time. It is important to note that the effect sizes of the associations between screen time and binge-eating disorder were relatively small. Screen time use and incidence of binge-eating disorder may rise after ages 9–11; thus, studies following the ABCD cohort into later adolescence will be an important area of future research. Although parent and child reports of binge eating tend to have low concordance (Bartholdy et al., 2017; Tanofsky-Kraff et al., 2005), parents are particularly important reporters for eating disorders in this age range (Barch et al., 2018) since young children may have less insight regarding their eating behaviors (Braet et al., 2007). The binge-eating questions came from a reliable and validated tool (KSADS-5) that was based on DSM-5 diagnostic criteria.

Conclusion

In a population-based, demographically diverse cohort of 9–10-year-old children in the U.S., we found that greater television and social media screen time was prospectively associated with binge-eating disorder at one-year follow-up. Given the rapid rise in screen time and disordered eating (Nagata et al., 2020; Termorshuizen et al., 2020) during the COVID-19 pandemic, future research should study these associations during the pandemic. Health care providers should assess for associations between excess screen time usage and binge eating and advise about potential risks associated with excessive screen time. Professional organizations, such as the American Academy of Pediatrics, should provide further specific guidance for families regarding screen time usage and strategies to prevent binge-eating disorder related to screen time usage (Chassiakos et al., 2016).

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can be found at https://abcdstudy.org/principal-investigators.html. ABCD consortium investigators designed and implemented the study and/or provided data but did not necessarily participate in analysis or writing of this report.

Data availability statement:

Data used in the preparation of this article were obtained from the ABCD Study (https://abcdstudy.org), held in the NIMH Data Archive (NDA). This is a multisite, longitudinal study designed to recruit more than 10,000 children aged 9–10 years and follow them over 10 years into early adulthood.

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Table 1.

Sociodemographic, screen time, and binge-eating characteristics of 11,025 Adolescent Brain Cognitive Development (ABCD) Study participants

	Total
Sociodemographic characteristics (baseline)	**Mean (SD) / %**
Age (years)	9.95 (0.63)
Sex assigned at birth (%)	
Female	48.8%
Male[a]	51.2%
Race/ethnicity (%)	
White	52.4%
Latino / Hispanic	20.1%
Black	17.3%
Asian	5.5%
Native American	3.2%
Other	1.5%
Household income (%)	
Less than $25,000	18.1%
$25,000 through $49,999	20.7%
$50,000 through $74,999	18.0%
$75,000 through $99,999	15.7%
$100,000 through $199,999	20.1%
$200,000 and greater	6.7%
Parent with college education or more (%)	79.7%
Body mass index (BMI) percentile	62.13 (30.70)
Screen time variables (hours per day, baseline)	
Total screen time	3.99 (3.16)
Television shows/movies	1.31 (1.31)
Videos (e.g. YouTube)	1.05 (1.18)
Video games	1.06 (1.13)
Texting	0.24 (0.56)
Video chat	0.21 (0.52)
Social networking	0.13 (0.45)
Binge-eating disorder, DSM-5	
Binge-eating disorder, baseline (%)	0.7%
Binge-eating disorder, one-year follow-up (%)	1.1%

Propensity weights were applied to yield representative estimates based on the American Community Survey from the US Census. SD = standard deviation

[a]Includes three participants whose sex at birth was intersex-male

Table 2.

Associations between baseline screen time and binge-eating disorder at one-year follow-up in the Adolescent Brain Cognitive Development Study

	Binge-eating disorder, unadjusted		Binge-eating disorder, adjusted[a]	
	OR (95% CI)	**p**	**aOR (95% CI)**	**p**
Total screen time (hours per day)	**1.13 (1.08–1.17)**	**<0.001**	**1.11 (1.05 – 1.18)**	**0.001**
Television shows/movies	**1.48 (1.24–1.77)**	**<0.001**	**1.39 (1.14 – 1.69)**	**0.001**
Videos (YouTube)	**1.23 (1.05–1.45)**	**0.01**	1.09 (0.89 – 1.32)	0.407
Video games	**1.22 (1.03–1.44)**	**0.019**	1.13 (0.90 – 1.41)	0.310
Texting	**1.48 (1.18–1.87)**	**0.001**	**1.40 (1.08 – 1.82)**	**0.011**
Video chat	**1.38 (1.11–1.72)**	**0.004**	1.32 (0.99 – 1.76)	0.057
Social networking	**1.66 (1.29–2.12)**	**<0.001**	**1.62 (1.18 – 2.22)**	**0.003**

Bold indicates p<0.05

[a]Covariates: race/ethnicity, sex, household income, parent education, BMI percentile, site, and baseline binge-eating disorder

2

Research Article

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The Power of the *Like* in Adolescence: Effects of Peer Influence on Neural and Behavioral Responses to Social Media

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University of California, Los Angele

FEATURES

Abstract

We investigated a unique w social media. We developed a novel functional MRI (fMRI) paradi aring tool, and measured adolescents' behavioral and neural respo sement and potential source of peer influence. Adolescents unde nitted to Instagram. They were more likely to *like* photos depicte nding showed the influence of virtual peer endorsement and held ors (e.g., drinking, smoking). Viewing photos with many (compar tivity in neural regions implicated in reward processing, social co n adolescents viewed risky photos (as opposed to neutral photos), sed. These findings highlight possible mechanisms underlying pee

Keywords

adolescent development, soc aging, open materials

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Social media are immensely popular among adolescents: Nearly 90% of American teens report being active users, and young people have continually outpaced other age groups in adopting new media (Lenhart, 2015). Given this prevalence, it is unsurprising that parents, educators, and the popular press have expressed concerns about the effects of social media on social-skill development and interpersonal interactions. Frequently, these concerns manifest themselves in questions about the effect of social media on the developing brain. Nonetheless, few studies have examined neural mechanisms underlying any kind of social-media use (Choudhury & McKinney, 2013; Mills, 2014).

The neural correlates of social-media use are particularly important to understand in the context of adolescence, and not only because adolescents are enthusiastic users. Adolescence is especially important for social cognitive development; it is theorized to be a sensitive period during which young people are uniquely attuned to the complexities of interpersonal relationships (Baird, 2012; Blakemore & Mills, 2014). Subcortical regions functionally associated with emotion processing and reward undergo considerable changes and reorganization during puberty (Brenhouse & Andersen, 2011; Sisk & Foster, 2004). The dopaminergic system and related regions in the striatum are implicated in

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Abstract

We investigated a unique way in which adolescent peer influence occurs on social media. We developed a novel functional MRI (fMRI) paradigm to simulate Instagram, a popular social photo-sharing tool, and measured adolescents' behavioral and neural responses to *likes*, a quantifiable form of social endorsement and potential source of peer influence. Adolescents underwent fMRI while viewing photos ostensibly submitted to Instagram. They were more likely to *like* photos depicted with many likes than photos with few likes; this finding showed the influence of virtual peer endorsement and held for both neutral photos and photos of risky behaviors (e.g., drinking, smoking). Viewing photos with many (compared with few) likes was associated with greater activity in neural regions implicated in reward processing, social cognition, imitation, and attention. Furthermore, when adolescents viewed risky photos (as opposed to neutral photos), activation in the cognitive-control network decreased. These findings highlight possible mechanisms underlying peer influence during adolescence.

Keywords

adolescent development, social cognition, social influences, risk taking, neuroimaging, open materials

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Social media are immensely popular among adolescents: Nearly 90% of American teens report being active users, and young people have continually outpaced other age groups in adopting new media (Lenhart, 2015). Given this prevalence, it is unsurprising that parents, educators, and the popular press have expressed concerns about the effects of social media on social-skill development and interpersonal interactions. Frequently, these concerns manifest themselves in questions about the effect of social media on the developing brain. Nonetheless, few studies have examined neural mechanisms underlying any kind of social-media use (Choudhury & McKinney, 2013; Mills, 2014).

The neural correlates of social-media use are particularly important to understand in the context of adolescence, and not only because adolescents are enthusiastic users. Adolescence is especially important for social cognitive development; it is theorized to be a sensitive period during which young people are uniquely attuned to the complexities of interpersonal relationships (Baird, 2012; Blakemore & Mills, 2014). Subcortical regions functionally associated with emotion processing and reward undergo considerable changes and reorganization during puberty (Brenhouse & Andersen, 2011; Sisk & Foster, 2004). The dopaminergic system and related regions in the striatum are implicated in

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potential mechanisms underlying two common features of adolescence: escalation in risk-taking behaviors and increased desire to spend time with and earn the approval of peers (Steinberg, 2008). For example, when adolescents completed a risky driving task alone or in the presence of peers, the presence of peers was associated with increases in both risk taking and activity in the nucleus accumbens (NAcc), a hub of reward circuitry (Chein, Albert, O'Brien, Uckert, & Steinberg, 2011). Smith, Chein, and Steinberg (2014) replicated these behavioral effects when peers were virtually connected, demonstrating that peer influence also occurs online (see also Cohen & Prinstein, 2006).

Less is known about how features unique to social media contribute to peer influence. For example, digital and in-person communication differ significantly in their affordance for quantifiable interactions. Whereas in-person communication is necessarily qualitative and involves subjective interpretation, many online environments allow for feedback that is purely quantitative. For example, a feature of most social media tools is the ability to *like* an image, text, or other piece of information, allowing for a simple, straightforward measure of peers' endorsement. For adolescents, who are particularly attuned to peer opinion, this *quantifiable social endorsement* may serve as a powerful motivator. Furthermore, quantifiable social endorsement provides a unique research opportunity: Although it is a form of interaction that occurs in the real world, it is simple enough to be experimentally manipulated.

The present study is, to our knowledge, the first to replicate social media interaction in the MRI scanner; however, important earlier work using behavioral and functional MRI (fMRI) methods has demonstrated how peer endorsement biases values (e.g., Campbell-Meiklejohn, Bach, Roepstorff, Dolan, & Frith, 2010; Izuma & Adolphs, 2013; Klucharev, Hytönen, Rijpkema, Smidts, & Fernández, 2009). In these studies, adults rated stimuli, then learned how other people rated the same stimuli, and finally rated the stimuli a second time. Participants changed their ratings to conform to those of peers or experts and showed greater NAcc activation during trials on which they agreed with these individuals than during trials on which they did not agree. Our study differs from previous work in that adolescents viewed content posted on social media simultaneously with information about its popularity—much as content is typically experienced online. We thus tested whether initial impressions were colored by the content's popularity and explored the overall effects of positive peer opinion on brain responses.

Specifically, we investigated the neural correlates of viewing photos with many or few *likes* to assess the role of quantifiable social endorsement in peer influence. We recruited adolescents to participate in an "internal social network" that simulated Instagram, a popular photo-sharing tool. Participants submitted their own Instagram photos, and they believed that all photos would be seen and liked by peers. We tested the possibility that the number of likes appearing under each photo would affect participants' responses. We hypothesized that participants would tend to like photos liked by more peers and refrain from liking less popular photos. We also hypothesized that neural responses to popular and unpopular photos would differ. Given previous research suggesting that peer presence heightens NAcc response (Chein et al., 2011), we predicted that viewing other people's photos that had a greater number of likes would similarly elicit greater NAcc activation. Evidence linking NAcc response to social evaluation (Meshi, Morawetz, & Heekeren, 2013) and sharing information about the self (Tamir & Mitchell, 2012), as well as the well-documented role of the NAcc in reward and reinforcement in general, suggests that viewing one's own popular photos would also elicit greater NAcc activity.

Peer influence is very important during adolescence; it is a means by which adolescents learn how to behave appropriately in their sociocultural environment. However, peer pressure can be maladaptive when it reinforces dangerous behaviors, such as drunk driving or drug use. Furthermore, young people frequently post content online depicting risky behaviors, and this may affect their peers' tendency to engage in such behaviors (Huang et al., 2014). Thus, we also investigated whether quantifiable social endorsement specifically influenced responses to risky behaviors by including photos depicting these behaviors. Well-established theories of adolescent risk taking suggest that the NAcc interacts with neural regions implicated in cognitive control during risky decision making (Casey, 2015; Steinberg, 2008). Accordingly, we directly compared adolescents' neural activity as they viewed risky images and neutral images to examine whether exposure to risky content online would influence activity in cognitive-control regions, regardless of the supposed popularity of the photos.

Method

Participants and fMRI paradigm

Thirty-four typically developing adolescents (18 female; age range = 13–18 years) participated in the present study. Two of these 34 participants were excluded from fMRI data analysis, 1 because of scan-console malfunction and 1 because of excessive motion. The sample size reflects the maximum number of participants that we were able to recruit given available funding, as well as timing constraints imposed by an institutional upgrade of the MRI magnet. Participants completed written consent in accordance with the institutional review board at the University of California, Los Angeles.

During recruitment, participants were informed that they would be involved in a study examining the brain's responses during social-media use. Participants were asked to submit photos from their own accounts on Instagram, a popular social-media tool used for sharing photos on mobile devices and the Internet. They were told that all of these photos would be combined to form an internal social network, that every participant would see a feed of these photos in the MRI scanner, and that the photos would appear as they did on Instagram. In reality, participants saw only some of their own photos while in the MRI scanner; all other stimuli were selected by the study team from among publicly available images on Instagram. During the laboratory visit, each participant was instructed that approximately 50 other adolescents had already viewed the feed of Instagram photos. This step was taken to establish the size of the audience, and to standardize how many likes would be regarded as many or few, irrespective of the size of a given participant's own social network. Participants were told that they could see how many times each photo was liked by previous participants and that the feed would be updated after their visit to reflect any new likes they contributed. In reality, the number of likes displayed under each image was assigned by the study team, as described later in this section.

The social-media task was presented to participants in the scanner using magnet-compatible 3-D goggles (VisuaStim; Resonance Technology, Inc., Northridge, CA) with a resolution of 800 × 640 pixels. The task mimicked the experience of browsing Instagram on a smartphone: Participants viewed a feed of photos, each of which was accompanied by text indicating how many other people had already liked the image. Photos were displayed one at a time on a white background accompanied by two on-screen buttons prompting the participant to choose "♥Like" to like the image or "→Next" to move on to the next image without liking it (Fig. 1). Images were presented for 3,000 ms, with an interstimulus interval that varied between 1,000 and 11,000 ms.

Participants saw 148 unique photos. These included 42 risky images and 66 neutral, nonrisky images. Risky photos depicted alcohol, cigarettes, marijuana, smoking paraphernalia, rude gestures, or adolescents (male and female) wearing provocative or skimpy clothing. Neutral photos depicted typical images (e.g., pictures of friends, food, and possessions) found on the social-media profiles of adolescents. Participants also saw 40 of the images they had submitted from their own Instagram accounts.

Across participants, all neutral and risky images were assigned both a popular value of 23 to 45 likes and an unpopular value of 0 to 22 likes. Two versions of the imaging paradigm were created: In Version 1, half of the photos in each category (risky, neutral) were displayed with a high number of likes and half were displayed with a low number of likes. In Version 2, the displayed popularity was opposite that in Version 1 (i.e., if a photo was displayed with many likes in Version 1, it was displayed with few likes in Version 2). Thus, half of the participants saw Version 1 of each image and half saw Version 2 of each image; this allowed us to hold the content and the aesthetic quality of the images constant while manipulating popularity.

To assign likes to participants' own images, author L. E. Sherman divided the 40 photos into groups on the basis of content (e.g., a people group or an objects group, depending on the participant). Then, each of the groups of photos was randomly split into two halves; one half was assigned many likes, and the other half was assigned few likes. Thus, the content of the popular and unpopular images was similar. Half of each participant's own photos appeared with 23 to 45 likes, and the other half appeared with 0 to 22 likes. Note that likes were not distributed continuously and evenly across the spectrum of 0 to 45. We did not expect neural and behavioral responses to vary linearly as the number of likes increased; instead, we hypothesized that participants would display qualitatively different responses to popular images than to unpopular images. Thus, we used a bimodal distribution of likes in which the majority was clustered between 30 and 45 likes (popular photos) or between 0 and 15 likes (unpopular photos). We chose to use a bimodal distribution to clearly differentiate popular and unpopular images. Of the 148 photos displayed during the scan, only 8 were depicted with intermediate values of 23 to 29 likes and 8 were depicted with 16 to 22 likes; these 16 images were included to avoid any suspicion among participants that might be caused by the obviously bimodal distribution. In light of our experimental manipulation, our categorical analyses reflect the difference between popular and unpopular images.

During the scan, participants were asked to view the images as they appeared and to decide whether they personally liked each image using the criteria they would normally use when deciding to like pictures on Instagram. Participants selected "♥Like" or "→Next" by pressing one of two buttons on a button box.

Data acquisition and analyses

Neuroimaging data were collected using a 3-T MRI scanner (Trio; Siemens Healthcare, Erlangen, Germany). The social-media paradigm was presented during a functional echoplanar, T2*-weighted gradient-echo scan lasting 11 min and 44 s (repetition time = 2,000 ms, echo time = 28 ms, flip angle = 90°, matrix size = 64 × 64, 34 axial slices, field of view = 192 mm, 4-mm slices with a 1-mm interslice gap). Button-press data were recorded in E-Prime

Fig. 1. Two examples of stimuli presented during the imaging paradigm. Participants saw innocuous photos of adolescents or everyday objects (e.g., the coffee drinks on the left) or images of objects related to risky behavior (e.g., the marijuana cigarette on the right) or adolescents engaging in risky behaviors. Images appeared as they would have in the Instagram app on a smartphone in the year 2014: The number of likes was displayed underneath each photo next to a heart icon, and the Instagram menu buttons were displayed beneath the likes. Finally, there were two buttons allowing participants to like an image ("♥Like") or to move on without liking the image ("→Next").

(Version 2.0; Psychology Software Tools, Sharpsburg, PA) and converted to IBM SPSS Statistics format for analysis. Binomial tests were used to determine whether participants conformed to peers' responses more often than would be predicted by chance. fMRI data were preprocessed and analyzed using the Analysis of Functional NeuroImages (AFNI; Version 16.0.00) software environment (Cox, 1996) and the Functional MRI of the Brain software library (FSL; Jenkinson, Beckmann, Behrens, Woolrich, & Smith, 2012). Preprocessing for each individual's data included image realignment to correct for head motion, normalization to the standard stereotactic space of the Montreal Neurological Institute's (MNI) 152-brain template, and spatial smoothing using a 5-mm full-width, half-maximum Gaussian kernel to increase signal-to-noise ratio.

For each participant, linear contrasts were calculated for several planned comparisons. Specifically, we modeled three linear contrasts comparing popular photos (many likes) and unpopular photos (few likes) in all three categories (i.e., neutral photos, risky photos, and participants' photos). In addition to modeling the six types of stimuli at the first level, we included several other parameters. These included the participant's button-press choice and reaction time for each trial and the luminosity of each image as determined using Adobe Photoshop. Group-level random-effects analyses were then conducted across all participants. At the group level, a prethreshold binary mask consisting of all regions exhibiting significant activity for any type of photo, compared with a fixation cross on a white background, was used to restrict our analyses to regions displaying significant task-related activity. Specifically, we first individually contrasted the six types of stimuli (e.g., neutral photos with many likes, neutral photos with few likes, risky photos with many likes) > fixation and then added the maps of each of these individual contrasts (thresholded at $z > 1.7$, corrected for multiple comparisons at $p < .05$) together. The final mask covered a considerable portion of the cortex and subcortex. Along with all of our group contrast maps, it is available for download at NeuroVault (http://neurovault.org/collections/RYSBTTMN/). We performed contrasts examining the effect of popularity (many likes > few likes and the reverse) for neutral photos, risky photos, and participants' photos. We also compared all neutral photos ostensibly submitted by peers with all risky photos ostensibly submitted by peers.

To test our a priori hypothesis that popular photos would elicit significantly greater activation in the bilateral

NAcc than unpopular photos would, we used a small-volume-correction approach. Our functional regions of interest (ROIs), derived from an independent sample of participants completing a monetary-incentive-delay task (Tamir & Mitchell, 2012), consisted of two 8-mm spheres in the left and right NAcc (MNI coordinates: $x = 10$, $y = 6$, $z = -4$, and $x = -8$, $y = 4$, $z = -6$, respectively). AFNI's 3dClustSim was used to determine that a contiguous cluster of 53 or more voxels was necessary to meet statistical criteria within these ROIs. To examine whether the many likes > few likes contrast differed significantly as a function of type of photo (neutral, risky, participant), we extracted parameter estimates (regression coefficients) from the bilateral ROIs for each contrast of interest and performed paired-samples t tests using IBM SPSS.

Results

To determine whether participants were significantly more likely than chance to match the supposed opinions of peers (i.e., to like popular images and to refrain from liking unpopular images), we conducted a series of binomial tests. Across all photos presented during the scan, participants matched their peers significantly more frequently than expected by chance ($p < .00001$). This effect was also significant for each individual type of photo, including neutral images ostensibly provided by peers ($p = .03$), images depicting risk-taking behaviors ostensibly provided by peers ($p = .03$), and the participants' own images ($p < .00001$). The effect was significantly larger for participants' own photos than for either neutral images, $\chi^2(1, N = 3{,}544) = 10.1$, $p = .001$, or risky images, $\chi^2(1, N = 2{,}736) = 6.6$, $p = .01$.

Neural responses also differed according to the number of likes for neutral, risky, and participants' own photos. Figure 2a depicts regions in which activity was significantly greater when photos were depicted as having garnered many versus few likes for neutral, risky, and participants' own photos. The regions of significantly greater activity for many likes compared with few likes differed by photo type. When participants viewed neutral photos with many likes, they showed significantly greater activity in the visual cortex extending to the precuneus and in the cerebellum (see Table S1 in the Supplemental Material available online). When participants viewed risky photos with many likes (compared with risky photos with few likes), significantly greater activity was found in one cluster in the left frontal cortex, extending from the precentral gyrus through the middle frontal gyrus and inferior frontal gyrus (Table S1). When participants viewed their own photos, significantly greater activity in response to photos with many likes (compared with photos with few likes) was observed in several regions (Table S1). These included areas implicated in social cognition, such as the precuneus, medial prefrontal cortex, left temporal pole, lateral occipital cortex, and hippocampus (Mars et al., 2012; Zaki & Ochsner, 2009), as well as reward learning and motivation, including the nucleus accumbens, caudate, putamen, thalamus, ventral tegmental area, and brain stem (e.g., Haruno & Kawato, 2006; Schott et al., 2008).[1] Table S1 includes a complete list of regions. For all three photo types, the reverse contrast (few likes > many likes) yielded no significant activation in the whole brain.

Neural responses also differed according to whether the photo depicted risky behavior (Fig. 2b). When participants viewed neutral images (compared with risky images) ostensibly submitted by peers, significantly greater activity was observed in bilateral occipital cortex, medial prefrontal cortex, and the inferior frontal gyrus (for a complete list of regions, see Table S2 in the Supplemental Material). When viewing risky images compared with neutral images (i.e., the reverse contrast), participants demonstrated significantly less activation in a network of regions implicated in cognitive control and response inhibition (e.g., Blasi et al., 2006; Bressler & Menon, 2010; Sherman et al., 2014), including dorsal anterior cingulate cortex, bilateral prefrontal cortex, and lateral parietal cortex (Table S2).[2]

In addition to whole-brain analyses, we conducted ROI analyses on the basis of our a priori hypothesis that photos depicted with many likes would elicit significantly greater activation in the bilateral NAcc than would those depicted with few likes. Consistent with our hypothesis, there was greater activity in the left NAcc when participants viewed neutral images that had many likes than when they viewed neutral images that had few likes. We also observed greater bilateral NAcc activation when participants viewed their own images for the many likes > few likes contrast. For images depicting risk-taking behavior, likes had no effect on brain response in the NAcc ROI. In the right NAcc, activation was significantly greater when participants viewed their own photos than when viewing other people's neutral images, $t(31) = 2.34$, $p = .026$, or risky images, $t(31) = 2.45$, $p = .02$, but did not differ significantly in the left NAcc (for all comparisons, $p > .10$).

Discussion

The present study highlights a new and unique way in which peer influence occurs on social media: through quantifiable social endorsement. We found that the popularity of a photo had a significant effect on the way that photo was perceived. Adolescents were more likely to like a photo—even one portraying risky behaviors, such as smoking marijuana or drinking alcohol—if that photo had received more likes from peers. This effect was

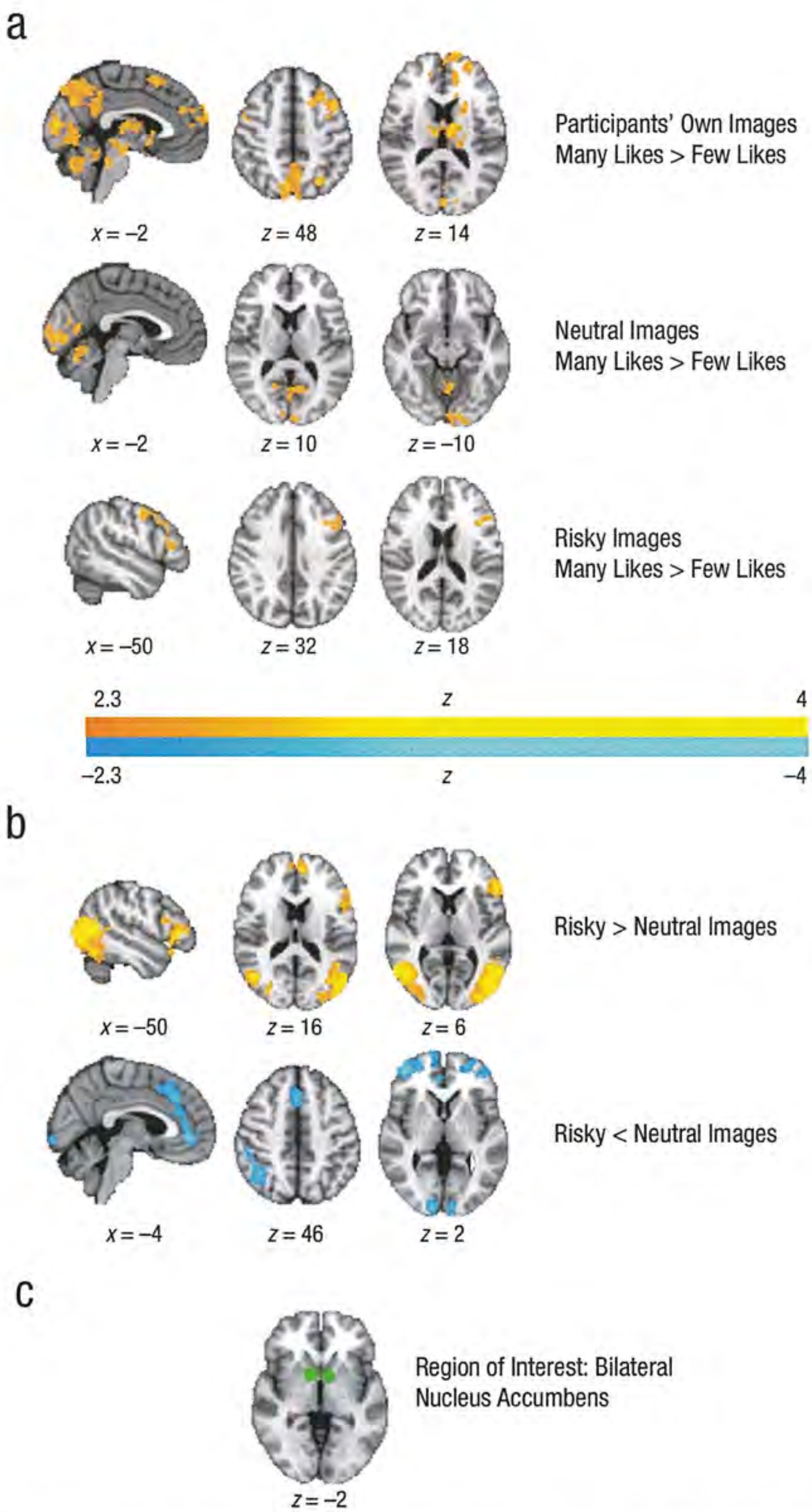

Fig. 2. Neural responses to Instagram photos with many likes compared with photos with few likes. The brain maps in (a) show neural regions with significant activity ($z > 2.3$, cluster corrected at $p < .05$) for the many likes > few likes contrast, for each of the three types of photos. The brain maps in (b) show neural regions with significant activity ($z > 2.3$, cluster corrected at $p < .05$) for the risky > neutral contrast and the risky < neutral contrast. Brain images are shown by radiological convention (i.e., left side of the brain is on the right). The brain map in (c) shows the location of the region of interest in the nucleus accumbens that was identified using a monetary-incentive-delay task in an independent sample of young adults (Tamir & Mitchell, 2012).

especially strong for photos the participants themselves had supplied. Adolescence is a period during which self-presentation is particularly important, including on social media; thus, this significantly greater effect may reflect the relative importance of self-presentation versus providing feedback to others.

Neural responses also differed according to number of likes. For all three types of photos, participants exhibited greater brain activity for photos with more likes. The regions of greater activity included areas implicated in social cognition and social memories, including the precuneus, medial prefrontal cortex, and hippocampus (Mars et al., 2012; Zaki & Ochsner, 2009), as well as the inferior frontal gyrus, which is implicated in imitation (Pfeifer, Iacoboni, Mazziotta, & Dapretto, 2008). When participants viewed their own photographs or neutral photographs ostensibly submitted by peers, greater activity in the visual cortex was observed in response to photos with many likes compared with photos with few likes, even though we controlled for photos' luminosity and content. The increased activation suggests that participants may have scanned popular images with greater care. Taken together, our imaging findings suggest that adolescents perceive information online in a qualitatively different way when they believe that this information is valued more highly by peers. The exact nature of these changes differs depending on the content depicted in the photo.

Our ROI analysis suggests that the NAcc, an important hub of the brain's reward circuitry, is implicated in the experience of receiving positive feedback on one's own images as well as viewing other people's images that have been endorsed by peers. The NAcc response, like our behavioral effects, was particularly robust for participants' own photos, suggesting that self-presentation can be especially rewarding and a motivation for using social networks (Manago, Graham, Greenfield, & Salimkhan, 2008). The popularity of risky photos (or lack thereof) had no differential effect on NAcc response. However, several participants in our adolescent sample reported no experiences with drugs and alcohol; this lack of familiarity may have contributed to the failure to detect a peer effect in the NAcc when comparing popular and unpopular risky images. Future research should examine the effect of popularity on NAcc response to risky photos in adolescents who report greater experience with drugs and alcohol.

Although quantifiable social endorsement is a relatively new phenomenon, we believe that the implications of this experiment extend beyond the digital context. Quantifiable social endorsement is a simple but nonetheless significant example of sociocultural learning; a like is a social cue specific to adolescents' cultural sphere, and adolescents use this cue to learn how to navigate their social world. Adolescents learn from quantifiable social endorsement in multiple ways, as evidenced by participants' differentiated neural responses to their own and other people's photos. Peers socialize one another to norms in multiple modes, including modeling appropriate behavior (behavioral display) and reinforcing appropriate behavior in other people (behavioral reinforcement; Brown, Bakken, Ameringer, & Mahon, 2008). Social media embody both modes of socialization: Adolescents model appropriate behavior and interests through the images they post (behavioral display) and reinforce peers' behavior through the provision of likes (behavioral reinforcement). Unlike offline forms of peer influence, however, quantifiable social endorsement is straightforward, unambiguous, and, as the name suggests, purely quantitative.

Although the present study does not allow us to directly compare in-person versus online peer influence, our findings are in line with results from previous research suggesting that the presence of peers heightens responses in reward circuitry and leads to differences in behavioral decision making (Chein et al., 2011). Furthermore, the present inquiry is, to our knowledge, the first to document that quantifiable social endorsement, a ubiquitous feature of social media, produces these measurable neural and behavioral effects. Future research should build on our findings to investigate how individual differences in neural response map onto behavioral outcomes: Can individual neural responses predict the degree of conformity that adolescents will demonstrate?

Sociocultural learning can be adaptive, in that it allows adolescents to flexibly learn from their environment. In the case of socialization to risky behavior, however, it can also be maladaptive. Multiple theoretical models (Casey, 2015; Steinberg, 2008) posit that risk taking in adolescence arises in part from heightened neural sensitivity to reward combined with immature capacity for cognitive control. In results that are in line with these models, we found that a network implicated in cognitive control (e.g., Seeley et al., 2007) was less active when participants viewed images depicting risky behavior (compared with neutral images). Certainly, viewing photos online does not, in itself, constitute a risk. It is therefore all the more striking that when simply viewing photos of risky behaviors ostensibly taken and posted by peers, adolescents exhibited decreased activation of the cognitive control network, possibly reflecting a mechanism by which peer behaviors disinhibit cognitive control in high-risk scenarios, thereby increasing the likelihood of engaging in risk taking. Future research should examine whether this decreased activation occurs into adulthood as well, or if this finding potentially reflects the immaturity of the prefrontal cortex in adolescence. Likewise, future research can shed light on whether the NAcc response to

social reward shown in the present study is particularly heightened in adolescence, in line with previous research on monetary reward (Braams, van Duijvenvoorde, Peper, & Crone, 2015).

Our findings and approach have implications not only for social media researchers, but also for those studying social cognition more broadly. Social media provide a compelling opportunity to examine social interaction in an ecologically valid context. Typically, in the confines of an MRI scanner, social interaction is limited and artificial. Because social media exist on a screen, however, they can be effectively imported into the scanner environment. Our study provides proof of concept for quantifiable social endorsement, a ubiquitous form of online interaction that is easily experimentally manipulated. Future research can build on this foundation to examine how neural responses to quantifiable social endorsement predict individual differences in a variety of behavioral and psychological domains.

Action Editor

Eddie Harmon-Jones served as action editor for this article.

Author Contributions

L. E. Sherman developed the study concept, and L. E. Sherman, M. Dapretto, and P. M. Greenfield contributed to the study design. Data collection was performed by L. E. Sherman, A. A. Payton, and L. M. Hernandez. L. E. Sherman and A. A. Payton performed the data analysis and interpretation under the supervision of M. Dapretto and P. M. Greenfield. L. E. Sherman drafted the manuscript, and M. Dapretto and P. M. Greenfield provided important revisions. All the authors approved the final version of the manuscript for submission.

Declaration of Conflicting Interests

The authors declared that they had no conflicts of interest with respect to their authorship or the publication of this article.

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Notes

1. The first set of regions also resembled the map for the term "social" on Neurosynth (http://neurosynth.org; a large-scale database of neuroimaging studies that provides meta-analytic reverse-inference analyses) as of January 2016 (Yarkoni et al., 2011). The second set of regions also resembled the map for the term "reward" on Neurosynth as of January 2016.
2. This set of regions also resembled the Neurosynth map for the term "cognitive control" as of January 2016.

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Picture Perfect: The Direct Effect of Manipulated Instagram Photos on Body Image in Adolescent Girls

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ABSTRACT

This study investigates the effect of manipulated Instagram photos on adolescent girls' body image, and whether social comparison tendency moderates this relation. A between-subject experiment was conducted in which 144 girls (14–18 years old) were randomly exposed to either original or manipulated (retouched and reshaped) Instagram selfies. Results showed that exposure to manipulated Instagram photos directly led to lower body image. Especially, girls with higher social comparison tendencies were negatively affected by exposure to the manipulated photos. Interestingly, the manipulated photos were rated more positively than the original photos. Although the use of filters and effects was detected, reshaping of the bodies was not noticed very well. Girls in both conditions reported to find the pictures realistic. Results of this study implied that the recent societal concern about the effects of manipulated photos in social media might be justified, especially for adolescent girls with a higher social comparison tendency.

Instagram is currently a very popular social network site, especially among teenagers (Seetharaman, 2015). Instagram allows its users to share photos and videos with others. Since its start in 2010, it has attracted more than 400 million active users, who upload around 80 million photos a day (Instagram, 2015). Photos and videos are a very direct form of online self-presentation and have become an increasingly powerful form of social online currency (Rainie, Brenner, & Purcell, 2012). Even though Instagram is the most popular photo sharing application on the Internet, it has received very little academic attention (Hu, Manikonda, & Kambhampati, 2014). This is surprising as Instagram has lately been a topic of concern in the public debate (Sass, 2014; Winter, 2013). The main concern involves the possibility to manipulate Instagram photos by using retouching techniques and, consequently, the potentially negative influence that these "perfect pictures" may have on body image of (young) Instagram users. In particular, both critics and fans frequently blame celebrities and models for using photo

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enhancement and retouching techniques. Hence, they normalize an unrealistic body ideal, which is problematic as they serve as role models for girls and young women (Sullivan, 2014).

Although in general, famous people have been criticized for manipulating self-images on social media, there are important reasons to investigate the effects of edited pictures of "ordinary" Instagram users. Research has indicated that men and women, both adolescents and adults, compare themselves more often to peers than to models or celebrities for social attributes (i.e., personality, intelligence) and physical attributes (i.e., weight, height, body image; Jones, 2001; Strahan, Wilson, Cressman, & Buote, 2006), and has thereby supported the general expectation from the social comparison literature that individuals generally prefer to make social comparisons to similar others (Miller, Turnbull, & McFarland, 1988). Furthermore, the comparison with peers might affect their body image in a comparable manner as media images do (Myers & Crowther, 2009). This might be due to the fact that peers are perceived more similar to themselves than celebrities and therefore are more relevant to compare themselves with. This is in line with the extensive identification literature, combining social cognitive theory (Bandura, 2002), the message-interpretation process model (Austin & Meili, 1994), and exemplification theory (Zillmann & Brosius, 2000). Shortly summarized, these theories state that when people perceive others to be more similar to themselves, identification and related cognitive and behavioral consequences are more likely to occur (see also Andsager, Bemker, Choi, & Torwel, 2006). This social influence mechanism might just as well apply to social media networks, as these are very popular environments for peer interaction. Research revealed that users of social media platforms often manipulate their appearance in the pictures they post online, and that this habit is especially prevalent among young girls (Manago, Graham, Greenfield, & Salimkhan, 2008; Philly Renfrew Center Foundation, 2014). However, the effects of exposure to enhanced social media photos of peers on young girls' body image are still largely unknown. Adolescent girls are often found to be particularly vulnerable for being influenced by media images (e.g., Borzekowski, Robinson, & Killen, 2000) because of the psychosocial development that is characteristic for this phase (Sturdevant & Spear, 2002). The present study attempts to further elucidate this relation by investigating the effects of exposure to original and manipulated Instagram photos of peers on adolescent girls' body image.

Earlier research focusing on body image has primarily investigated the influence of exposure to idealized thin bodies in advertisements, magazines, television, as well as music videos on young women's body image. These studies often revealed a relation between exposure to the thin ideal and a negative body image among young girls and women (e.g., Grabe, Ward, & Hyde, 2008; Halliwell & Dittmar, 2004; Irving, 1990;). This effect can be explained by the negative contrast theory, stating that women experience a contrast between themselves and the thin, idealized models and that this

leads to lower body satisfaction (Thornton & Maurice, 1999; Thornton & Moore, 1993). However, some studies actually found self-enhancing effects of exposure to thin ideal images (e.g., Henderson-King & Henderson-King, 1997; Joshi, Herman, & Polivy, 2004; Mills, Polivy & Tiggemann, 2002; Myers & Biocca, 1992). Based on these findings, an alternative to the negative contrast theory was formulated by Mills et al. (2002), suggesting that thin media models might cause a "thinness fantasy" (Myers & Biocca, 1992) by inspiring women for whom thinness is self-relevant. Ample research has studied the effects of media models on body image, but the effects of exposure to images on social media sites are not well established. As traditional media are surpassed in popularity by online social media platforms, especially among young people, it becomes important to include these newer forms of media in this line of research as well (Fardouly & Vartanian, 2015; Seetharaman, 2015; Tiggemann & Slater, 2013).

One important characteristic that sets social media apart from other studied media types is the strong focus on peer interactions. Media models, that is, models and celebrities, are often presented as unrealistic standards of beauty in for example media literacy programs and the public debate, because of the well-known editing and retouching techniques used when displaying media models (e.g., Thompson & Heinberg, 1999; Yamamiya, Cash, Melnyk, Posavac, & Posavac, 2005). Less known is that "ordinary" social media users also use these techniques, as a part of impression management in self-presentation (Manago et al., 2008; Won Kim & Chock, 2015). Girls who compare themselves with manipulated photos of peers might think they are comparing themselves with people who are similar to them, rather than with celebrities whose bodies are seen as unattainable (Jones, 2001). However, one might conclude that the appearances of these peers might be not realistic at all. The current study investigates whether manipulated—and thereby idealized—Instagram photos of peers affect body image in young women. In line with earlier studies on exposure to idealized images, it is expected that:

H1: Exposure to manipulated Instagram photos leads to lower body satisfaction in adolescent girls than exposure to original photos.

Previous research also revealed that the effects of exposure to the thin ideal in traditional media depend on individual susceptibility factors (e.g., Henderson-King & Henderson-King, 1997; Joshi et al., 2004; Myers & Biocca, 1992; Wilcox & Laird, 2000). Especially the tendency to engage in social comparisons (Social Comparison Theory; Festinger, 1954) has proven to be influential in the relation between exposure to the thin ideal in the media and women's body dissatisfaction (e.g., Keery, Van den Berg, & Thompson, 2004; Won Kim & Chock, 2015).

It is often found that body dissatisfaction is a result of young women's upward social comparisons of their own appearance with the appearance of other young women in real life or in a (social) media context (e.g., Dittmar & Howard, 2004; Fardouly, Diedrichs, Vartanian, Halliwell, 2015; Fardouly & Vartanian, 2015; Mabe, Forney, & Keel, 2014; Tiggemann & Miller, 2010; Tiggemann & Slater, 2013; Vartanian & Dey, 2013). More precisely, women who more frequently engage in comparisons with others are also more negatively affected by exposure to idealized images of others, compared to women who engage in these comparisons less frequently (Dittmar & Howard, 2004). Therefore, the current study examines whether women's social comparison tendency moderates their responses to manipulated Instagram photos. It is expected that:

H2: The negative effect of exposure to manipulated Instagram photos compared to original Instagram photos on body satisfaction is stronger for girls with higher social comparison tendency.

Method

An online experiment was conducted to investigate the effect of manipulated Instagram photos on the body image of girls. The experiment has a 2 (Instagram photos: original versus manipulated) × 2 (social comparison tendency: lower vs. higher) between-subjects design. Participants were randomly exposed to either 10 original Instagram photos (N = 72) or to 10 manipulated photos (N = 72). Subsequently, they answered a number of questions through an online survey.

Participants and procedure

A total number of 144 adolescent girls participated in the experiment. Their age ranged between 14 and 18 years old (M = 15.92; SD = 1.16). The girls in our sample attended different levels of secondary education. In The Netherlands—where this study was conducted—children are divided over different educational levels at secondary schools based on their achievement scores obtained at elementary schools (cf. Scheerens, Luyten, & Van Ravens, 2011). Students can either attend pre-vocational secondary education (the lowest level, preparing for vocational education), general secondary education (middle level, preparing students for universities of applied sciences), or pre-university education (highest level, preparing student for research universities). As the transition from elementary to secondary school usually takes place at the age of 12, the girls in our sample attended at least of few years of secondary education at a specific level of secondary

education. This makes it important to take level of education into account. The girls in our sample were almost equally divided over the three levels of education that could be discerned: 49 girls attended a low level of education, 50 girls had a medium level of education, and 45 girls attended the highest level of education. The division of age over the different levels of education was somewhat skewed: The lower educated participants were somewhat younger ($M = 15.18$; $SD = .81$) than participants attending the middle ($M = 16.22$; $SD = .93$) or highest level ($M = 16.40$; $SD = 1.32$) of education. This can be explained by the fact that education at the lowest level takes 4 years to complete, whereas education at the middle (5 years) and highest level (6 years) takes longer. Therefore, students at the latter two levels can be older when attending secondary education. Preliminary analyses, however, showed that the small differences in the division of age over the three levels of education did not play a role of interest in the analyses.

Snowball sampling was used to recruit participants. We first invited girls from our own network to participate. Next, we asked them whether they knew other girls aged between 14 and 18 years old that might want to participate. Because most of the participants were under the age of 18, active parental consent was always asked for prior to the start of the data collection. This procedure is in accordance with the guidelines as formulated by the ethics committee of Faculty of Social Sciences (ECSS) at Radboud University. After obtaining permission from parents, girls received an email containing further information about the study and a link to the online experiment.

In the invitation email, a cover story was used to inform them about the research, as it was important not to reveal the real aim of the study. Participants were told that the study goal was to investigate how contextual factors affect preferences for different face types, and that they therefore would be exposed to pictures of people with different facial expressions. The email also contained instructions about the procedure they had to follow while taking part in the study. We asked them to complete the task at a moment that they were in a quiet area, without disturbing factors in their surroundings. In addition, they were asked to focus on the experiment only and to avoid interruptions.

After clicking on the link to start the experiment, a short instruction was presented on the screen. We repeated the (false) study aim and told them that the study started with showing them 10 Instagram photos, either original or manipulated. We asked each participant to take enough time to carefully look at the photos, and informed them that subsequently a number of questions would be asked. We emphasized that all information provided would be treated confidentially. After completing the study, participants were thanked for their voluntary participation. Moreover, they were offered the possibility to contact the researchers through email in case they wanted to have more information or to ask additional questions about the study.

Materials

The stimulus materials consisted of 10 "selfies" (self-portrait photos taken with a digital camera or camera phone held in the hand; Saltz, 2014). Selfies were used because photos in this format are a popular trend on Instagram and other social network sites (Hu et al., 2014). A teenage girl was the only person present in the picture. Social comparison requires similarity between the observer and the persons that is observed (Suls, Martin, & Wheeler, 2002), implying that that the girls participating in the study are more likely to compare themselves with females having a comparable age. In Dutch society, the majority of the population is native Dutch and predominantly has a light skin color and Caucasian ethnicity (Centraal Bureau voor de Statistiek, 2015). We, therefore, only used sample images from women with a light skin color. The selected photos may therefore increase the change of social comparison, which is important in light of the study aim. Inspired by Fardouly et al. (2015), another criterion that was applied to the selection of stimulus materials was that photos varied in the parts of the body that were emphasized. Five photos particularly emphasized the girl's face, skin, and hair; the other five highlighted the whole body (see examples in Figure 1).

To create the manipulated photos, each original photo was edited. To this end, effects and filters that are available on Instagram were used. Instagram provides a high number of options to improve pictures. Possibilities include, but are not limited to, improving the color intensity, brightness, and adding strong shadow. Moreover, according to frequently used altering techniques (Philly Renfrew Center Foundation, 2014), we edited the faces and bodies visible in the photos, by removing eye bags, wrinkles, and impurities, and by reshaping legs to be thinner and waist to be slimmer. Finally, all photos were displayed in the same Instagram format. However, we removed comments

Figure 1. Examples of original versus manipulated Instagram photos emphasizing face, skin, and hair (left), or body (right).

that are normally presented along with photos on Instagram, and gave all materials the same number of likes to exclude this factor as a possible confounder.

Measures

Body image was the dependent variable in the study. The Body Image State Scale (Cash, Fleming, Alindogan, Steadman, & Whitehead, 2002) was used to measure girls' evaluation and affect about their physical appearance at this moment. Girls indicated their (dis)satisfaction with their overall physical appearance; (dis)satisfaction with their body size and shape; (dis) satisfaction with their own weight; feelings of physical (un)attractiveness; current feelings about their own looks relative to how one usually feels; and their evaluation of their appearance relative to how the average person looks. Following Cash et al. (2002), a 9-point, bipolar, Likert-type scale was used with a higher score indicating a more positive body image. As expected, results of a factor analysis including the six items yielded one factor. The initial eigenvalue of this factor (3.341) indicated that this factor explained 55.69% of the variance (factor loadings >.47). In addition, Cronbach's alpha was sufficient (α = .83). We, therefore, calculated the participant's mean score on the statements to construct the variable body image (M = 4.68; SD = 1.26).

To measure girls' *social comparison tendency*, the Iowa–Netherlands Comparison Orientation Measure (Gibbons & Buunk, 1999) was used. This scale consists of 11 items, measured with a 5-point Likert scale ranging from (1) *totally disagree* to (5) *totally agree*. These 11 items were:

(1) I often compare myself with others with respect to what I have accomplished in life;
(2) If I want to learn more about something, I try to find out what others think about it;
(3) I always pay a lot of attention to how I do things compared with how others do things;
(4) I often compare how my loved ones (boy or girlfriend, family members, etc.) are doing with how others are doing;
(5) I always like to know what others in a similar situation would do;
(6) I am not the type of person who compares often with others;
(7) If I want to find out how well I have done something, I compare what I have done with how others have done;
(8) I often try to find out what others think who face similar problems as I face;
(9) I often like to talk with others about mutual opinions and experiences;

(10) I never consider my situation in life relative to that of other people; and

(11) I often compare how I am doing socially (e.g., social skills, popularity) with other people.

The scores on item 6 and item 10 were reversed prior to the analyses. Results of a factor analysis yielded two dimensions. However, the second dimension consisted of only one statement: I often like to talk with others about mutual opinions and experiences. We decided to exclude this item and, thus, to construct the variable based on the remaining ten items ($\alpha = .87$). Additionally, we created two groups (lower vs. higher tendency) by using a mean split ($M = 3.22$; $SD = .90$) to make this variable suitable for the analysis. As a result, 63 girls were indicated as having a lower tendency to make social comparisons, the other 81 girls as having a higher tendency to compare themselves with others.

Level of education is included as control variable in the analysis, as a correlation was found between educational level and the dependent variable ($r = .388$; $p < .001$). Those with a higher level of education generally had a more positive body image.

Results

Manipulation checks

For the manipulation check, we asked the 144 girls that participated in the study to respond on a scale ranging from (1) *totally disagree* to (5) *totally agree* to several statements about the photos. First, we asked them to what extend they agreed with the statement that the Instagram photos were manipulated by using filters. Results of a t test showed that their agreement with this statement was higher for the manipulated photos ($M = 4.51$; $SD = .77$) than for the original photos ($M = 2.19$; $SD = 1.21$), $t(142) = -13.759$; $p < .001$. In addition, girls gave higher agreement to the statement that effects (e.g., adding color to look less pale, improving brightness) were used for the manipulated ($M = 4.44$; $SD = .82$) than for the original photos ($M = 2.11$; $SD = 1.15$), $t(142) = -14.055$; $p < .001$. This implies that we were successful in making a distinction between the original and the manipulated photos in this regard. We also asked the participants whether the faces and bodies in the photos were manipulated in terms of reshaping. t tests showed that it was harder to detect these adaptations in the manipulated photos, as the differences compared to the original photos were only marginally significant. For faces, manipulated photos scored somewhat higher ($M = 1.82$; $SD = .81$) than the original photos ($M = 1.61$; $SD = .70$), $t(142) = -1.674$; $p = .051$. In addition, participants slightly more agreed with the statement that bodies were reshaped for the manipulated ($M = 1.76$; $SD = .83$) than for the original $M = 1.60$; $SD = .64$) photos, $t(142) = -1.347$; $p = .090$.

Descriptive Results

Prior to reporting the results of the hypotheses testing, we provide some general information about the girls' evaluation of the photos. First, results of a t test showed that girls in the manipulated photos condition rated the photos as more pretty on a 5-point Likert scale ($M = 4.25$; $SD = .69$) than girls in the original photos condition ($M = 3.75$; $SD = .62$), $t(142) = -4.577$; $p < .001$. In addition, the manipulated Instagram photos were perceived as more attractive ($M = 4.57$; $SD = 1.69$) than the original photos ($M = 3.38$; $SD = .67$), $t(142) = -7.533$; $p < .001$. We also found that girls are generally unaware that Instagram photos might be manipulated. To be more specific, for both original and manipulated photos, they agree with the statement that the photos provide a representative view of reality ($M_{original} = 3.68$; $SD_{original} = 1.11$ vs. $M_{manipulated} = 3.72$; $SD_{manipulated} = 1.20$ on a 5-point Likert scale ranging from (1) *totally disagree* to (5) *totally agree*), $t(142) = -.216$; $p = .829$. In addition, no differences were found regarding the statement that the photos paint a picture that is better than reality, $t(142) = -.718$; $p = .474$. The means for both original ($M = 2.22$; $SD = .109$) and manipulated photos ($M = 2.36$; $SD = 1.23$) showed that they generally disagree with this statement.

Effects of manipulated instagram photos

To test the hypotheses, a one-way analysis of covariance was performed with body image as dependent variable, Instagram photo manipulation and tendency to make social comparisons as between-subjects factors, and level of education as covariate. Participant age was excluded as additional covariate because preliminary analyses showed no effects of age on the dependent variable body image. Hypotheses were tested at the alpha = .05 level (one-tailed).

The first hypothesis predicted that girls would have lower body satisfaction after exposure to manipulated Instagram photos than original photos. This hypothesis was supported, $F(1,139) = 4.252$; $p = .021$; $r = .17$. Girls exposed to the manipulated photos showed to have a significant lower body satisfaction ($M = 4.57$; $SE = .13$) compared to girls exposed to the original photos ($M = 4.94$; $SE = .13$). Results additionally showed that level of education (included as control variable) significantly affected body image, $F(1,139) = 14.618$; $p < .001$; $r = .31$. Descriptive statistics showed that a higher the level of education correlates with a more positive body image.

The second hypothesis concerned the moderating effect of the tendency to make social comparisons. First, a main effect of social comparison tendency on body image was found, $F(1,139) = 18.828$; $p < .001$; $r = .35$. Girls who have a higher tendency to compare themselves with others have a lower body

image (M = 4.35; SE = .12) compared to those who have a lower social comparison tendency (M = 5.15; SE = .14). In addition, results provided support for the expectation that the negative effect of manipulated Instagram photos on body image exposure are stronger for girls with a higher social comparison tendency, $F(1,139) = 3.890$; $p = .025$; $r = .16$.

As shown in Figure 2, post-hoc F tests (pair-wise comparisons with Bonferroni correction of the interaction categories) indicate that the body image of girls with a higher tendency to make social comparisons is more negatively affected by manipulated Instagram photos (M = 3.98; SE = .17) than by original photos (M = 4.72; SE = .18), $F(1,139) = 9.209$; $p = .002$; $r = .25$. In contrast, girls with a lower tendency to make social comparisons did not significantly differ in body image after exposure to either manipulated (M = 5.16; SE = .18) or original photos (M = 5.15; SE = .21), $F(1,139) = .001$; $p = .485$; $r = .00$. Moreover, results revealed that the negative effect of manipulated photos is more prevalent among girls with a higher tendency to make social comparisons, $F(1,139) = 18.777$; $p < .001$; $r = .34$. Original photos also affected the body image of these girls more compared to ones with a lower tendency to make social comparisons, but this influence is weaker, $F(1,139) = 3.016$; $p = .043$; $r = .15$. In all, the effect of manipulated Instagram

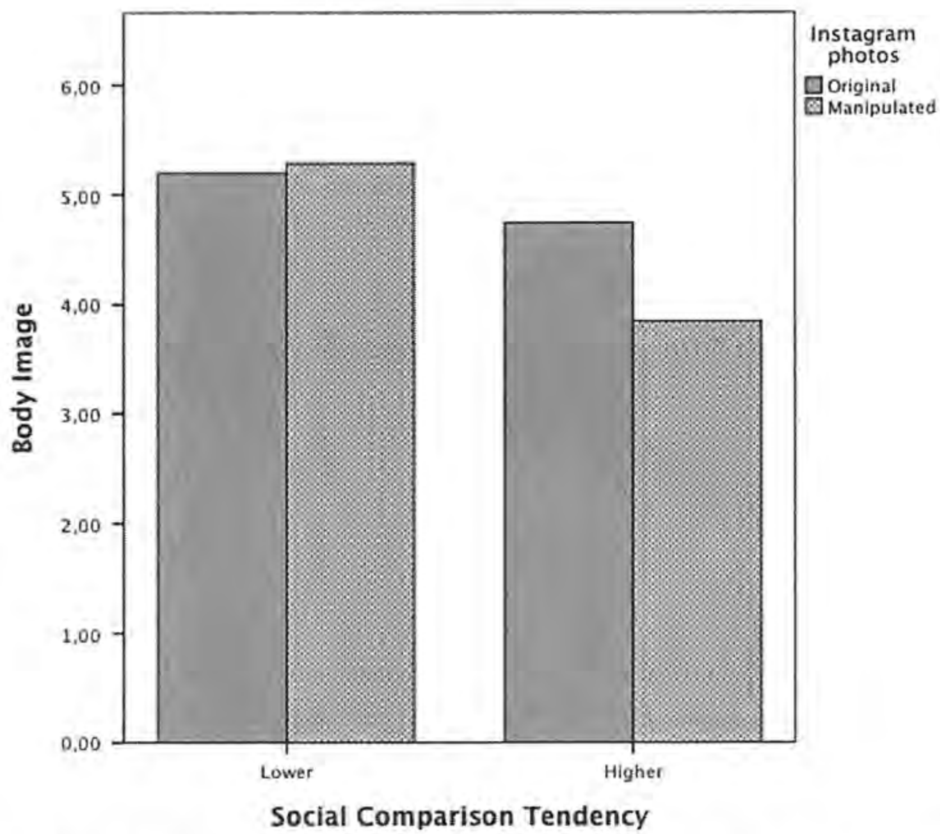

Figure 2. Effect of manipulated versus original Instagram photos on body image among girls with a lower and higher social comparison tendency.

photos on body image exposure is stronger for girls with higher social comparison tendencies.

Discussion

The current study set out to investigate whether manipulated Instagram photos have a negative effect on the body image of female adolescents and whether those with a higher tendency towards social comparison are more vulnerable in this regard. It can be concluded from the results that exposure to manipulated Instagram photos indeed leads to lower body satisfaction in comparison to exposure to non-manipulated selfies from online peers. This particularly related to girls with a higher tendency to make social comparisons. The body image of girls with a lower tendency to compare themselves with others was about equal after exposure to either original or manipulated Instagram photos. In contrast, girls with a higher tendency to make social comparisons had a lower body image in general, and especially after exposure to the manipulated Instagram photos.

These results imply that the common practice of Instagram users to manipulate and tweak their appearance in pictures can have negative consequences, at least for the girls who are prone to make social comparisons. It is worrisome that even short exposure to unfamiliar peers in a research setting can lead to direct changes in body image. The fact that girls believed that the presented Instagram photos showed a representative view of reality and did not notice reshaping of the bodies very well reinforces these concerns. Adolescence is a critical period for psychosocial development and earlier research showed that girls in this phase are more vulnerable for media influences because they equate their own bodies with media images (e.g., Borzekowski et al., 2000). The frequent use of social media networks such as Instagram among young girls (Seetharaman, 2015) clearly stresses the importance of studying the effects of exposure. These results might imply recommending including a disclosure when opening an Instagram account that would remind users that the images on Instagram are often retouched and manipulated, as a means of visual literacy and thereby possible protection from harmful effects. However, following the results of the study by Harrison and Hefner (2014), who reported harmful effects (i.e. lower physical self-esteem and higher body consciousness) of these so called retouched-aware photos, this recommendation might lead to undesirable effects. Therefore, more research is needed to unravel how to best protect these young girls from the negative effects of retouched (social) media images.

The findings of the current study are in line with results found in studies on the effects of exposure to idealized thin bodies in traditional media as well as the first studies on social media networks (i.e. Fardouly et al., 2015; Fardouly & Vartanian, 2015). These studies showed that exposure to

idealized media images lead to a greater focus on the body and more uncertainty among females (Hargreaves & Tiggeman, 2004, Thompson & Heinberg, 1999), which consequently may lead to higher body dissatisfaction (Knauss, Paxton, & Alsaker, 2008). An important difference, however, is that the girls in the current study compared themselves with similar young women (unfamiliar peers), and not with models or celebrities showing the well-known unrealistic beauty standards. In line with earlier findings, the effects of social comparisons may be stronger when perceived similarity is high, which might be the case with exposure to images of peers in social media (see also Andsager et al., 2006; Montoya, Horton, & Kirchner, 2008). Fardouly and colleagues (2015) also argue that the appearance of peers in social media environments is seen as more attainable and, therefore, and more directly triggers social comparison. A suggestion for future research would be to include measures of perceived similarity and attainability to examine this assumption.

Limitations of the current study may also help to shape the future research agenda. First, the current study investigated a short-term effect of exposure to Instagram photos. Therefore, it remains unclear whether this effect will also exist in the longer term. As girls and young women are frequently exposed to Instagram photos (cf. Instagram, 2015), the effect might be even stronger in the long run. Future research should provide more insight into the long-term effects of exposure to Instagram photos on the body image of girls. This research should also strive to assess the general social media habits of the girls involved, to validate if market research positioning of Instagram as the preferred type of social media for girls this age is accurate (Piper Jaffray, 2014; Turpijn, Kneefel, & van der Veer, 2015). In addition, it would be interesting to focus on the effect of Instagram photos presenting people that participants know personally, instead of (only) exposing them to people they are not familiar with. Girls using Instagram are also frequently exposed to photographs of people from their own network, such as friends, classmates, and peers (Madden et al., 2013). One might argue that it is more likely that girls realize that photos are manipulated when they are exposed to photos of people they know, as it is easier to notice that the person in Instagram photos look different than in reality. As a consequence, it is possible that the manipulated photos have a less negative effect on the body image of girls. However, it is also possible that girls have a higher tendency to compare themselves with people from their personal network compared to people they do not know, because of higher perceived similarity and social relevance.

Related to this, our results showed that girls were—at least to some extent—unable to truly detect the retouching of the bodies of the pictures. Although this is in accordance with "real" media pictures (e.g., in magazines) in which retouching is used, this might still be a limitation of our

study because we cannot totally rule out the possibility that our manipulation was too subtle to detect and the effects are solely explained by other factors (e.g., the filters used). However, we considered the manipulation substantial enough to be a valid reflection of reality and the fact that we found differences in body satisfaction shows that although the manipulation might not be truly explicitly perceived, it still can affect the viewer. Following up on this issue, an interesting discussion in this light is how reality is exactly defined. Edited and retouched photos might have become so widely accepted and, therefore, normal for contemporary teenagers (e.g., Choi, 2016; Sutton, Brind & McKenzie, 2007; Wheeler, 2005), that it is hard to tell whether these pictures actually deviate from their view of reality as an issue separate from whether the retouching is detected or not. Related to the recent development that not only celebrities and models, but also peers and teens themselves can idealize their images through retouching, it might even be the case that the distinction between these groups (celebrities vs. peers) in terms of identification and comparison becomes much less profound as the differences between the images become smaller. To investigate this hypothesis, future studies could focus on further examining the changing roles of celebrities versus peers as targets of (appearance-related) comparisons.

Furthermore, the participants were told that the study goal was to investigate how contextual factors affect preferences for different face types, and that they, therefore, would be exposed to pictures of people with different facial expressions. Although we believe that our cover story distracted the participants from (guessing) the real purpose of the study, we are aware of the fact that demand still might have played a role, as exposure to the pictures was followed by the social comparison and body image questions. Demand has been studied in this line of research and some evidence suggests that participants tend to engage in upward comparisons when the study purpose is more obvious rather than less (Mills et al., 2002). It is possible that upward comparisons were stimulated in the present study by asking questions about making comparisons after exposure, although demand characteristics were not explicitly present like in the experiment by Mills et al. (2002). Still, it is very important to pay attention to this topic and to try to avoid demand characteristics as much as possible in future studies. It would also be helpful to ask the participants at the end of the study what they consider the goal of the study, to investigate to what extent they are aware of the purpose. In addition, future studies should include a control condition in which participants are exposed to neutral pictures (e.g., showing landscapes) or not exposed to pictures at all (cf. Harrison & Hefner, 2014), to establish baseline scores on body image in the sample. These baseline scores can serve as a true reference point, since exposure to selfies (edited or not) in itself can affect body image.

Another suggestion for future research would be to include a measure that specifically investigates appearance-related comparison tendencies, for example the Physical Appearance Comparison Scale-Revised (PACS-R, Schaefer & Thompson, 2014). In the current study, we focused on general social comparison tendencies, but we know from the literature that social comparison can manifest itself in many different target domains (Wood, 1989) of which appearance is one that might be particularly interesting in the light of the present study. Using an appearance-related comparison measure might result in even stronger moderating effects than general comparison tendencies, as scoring high on this specific domain of social comparison suggests that girls might have a higher risk of being influenced by social media photos picturing ideal bodies as they specifically compare themselves with others with respect to appearances (e.g., Myers & Crowther, 2009). A final recommendation for future research would be to include ethnicity of the participants as a possible moderator and also include a larger variety of ethnicities in the stimulus material. It is important to include ethnicity in future research because research has shown that both weight-related and general appearance body image varies among ethnic groups (cf. Altabe, 1998; Cachelin, Rebeck, Chung, & Pelayo, 2002; Miller et al., 2000).

In sum, this study contributes to the existing literature regarding media influence on body image in adolescent girls by examining the effects of exposure to Instagram photos of peers. Photo and video sharing becomes more and more common among (young) social network users, so it is important to establish its effects. In addition, the results of the present study add to the public discussion about the use of retouching and reshaping techniques in social media self-presentation materials. The findings indicate that not only celebrities exert influence because they serve as role models, but we should also seriously consider the influence of (unfamiliar) peers.

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REVIEW Open Access

Photo editing and the risk of anorexia nervosa among children and adolescents

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Abstract

Filters and photoediting are widely used to transform or alter photos, mainly selfies, before sharing with friends or on social networks. In adult population there is a strong evidence of the potential risks of this behaviuor. Aim of the present work is to revise international literature exploring the correlation between photo manipulation and anorexia nervosa among children and adolescents. International literature focusing on photo manipulation and anorexia nervosa has been examined, according to the PRISMA Extension guidelines for Scoping Reviews using the following strategies: "Photomanipulation" Filters: English, Child: 6–12 years, Adolescent: 13–18 years, from 2000–2024 Pubmed Search: (("Photography"[Mesh]) AND "Anorexia Nervosa"[Mesh]) AND "Anorexia Nervosa"[Majr] Filters: Adolescent: 13–18 years, Child: 6–12 years, from 2000–2024. According to the literature review strategy, only few and limited evidences are available for the pediatric population. As well as in adults, there is an increased risk for eating disorders in adolescents regularly sharing selfies and practicing photo manipulation. New social media and online chat may be associated with lower personal weight satisfaction, higher drive for thinness, and eating disorder symptoms. The Italian Pediatric Society Communication Group suggests to increase the awareness on the potential risks of photo manipulation among children and adolescents, suggesting the plan of more studies target to this population to gain evidence specifically, social campaigns and school education. Finally, the use of technology should be included as part of routine pediatric control visit, especially in the pre-adolescence period.

Keywords Photomanipulation, Anorexia nervosa, Children, Adolescents, Social media

Background

Photo manipulation is defined as the process of transforming or altering a photograph - especially selfies - by using editing programs, software or apps before sharing it, in order to achieve desired results [1]. This may range from basic retouching, like light adjustments or cropping, to more complex processes. Editing tools and apps directly integrated into smartphones make photo manipulation extremely easy, allowing to remove imperfections, add filters, correct brightness, etc. While photo manipulation offers exciting prospects for creative expression and innovation, its power to distort reality raises issues regarding societal perceptions and reality distortion. In fact, by using editing tools and image filters built into various apps, users can make themselves look differently from how they really are, creating unrealistic profiles. The main risk associated to photo manipulation is indeed perpetuating unrealistic beauty standards. There are even photo editing applications that use artificial intelligence to fully alter the physical aspect. In this case, technology choses which physical features require modification, potentially decreasing self-esteem. In fact, people may discover flaws in themselves that not have

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noted before [2]. Over the past few years, social media have increasingly become an integral part of our lives, often representing a showcase through which displaying a "perfect and happy" version life, propagating appearance-focused contents, thus encouraging creators to modify their photos to impress others. Edited photos are frequently shared using social media and findings from studies involving adults support the correlation between social media posting of edited selfies and worse women's perception of body image and satisfaction with body size. Existing literature has proved that women that are more prone to social media photo editing report greater disordered eating attitudes and behaviors [3]. Moreover, Facebook behaviors may also be associated to bulimic symptoms and overeating episodes [4]. In addition, social media contents related to appearance can have an impact on body image perception and also on cosmetic surgery intention, since body image dissatisfaction may encourage subjects to search for remedies to their disorder, such as cosmetic procedures or surgery. As demonstrated by Herman et al. in a study involving 470 Instagram users aged 18–25 years, passive (e.g., following influencers) and active (e.g., frequency of using Instagram filters) use of highly visual social media are associated with an increased acceptance and normalization of cosmetic procedures, as well as the hypothetical intention to undergo them [5]. Moreover, body dissatisfaction predicts the development of eating disorder symptoms in young adults, representing a strong risk factor for those disorders [6].

Aim of the present work is to revise international literature exploring the correlation between photo manipulation and and anorexia nervosa among children and adolescents.

Materials and methods

International literature focusing on photo manipulation and anorexia nervosa has been examined.

This scoping review has been performed according to the PRISMA Extension guidelines for Scoping Reviews (Jones, M.E. LibGuides: Creating a PRISMA Flow Diagram: PRISMA. 2020. Available online: https://guides.lib.unc.edu/prisma/step-by-step).

An electronic search was undertaken on PubMed database on 24th April 2024 using the following strategies: "Photomanipulation" Filters: English, Child: 6–12 years, Adolescent: 13–18 years, from 2000–2024 Pubmed Search: (("Photography"[Mesh]) AND "Anorexia Nervosa"[Mesh]) AND "Anorexia Nervosa"[Majr] Filters: Adolescent: 13–18 years, Child: 6–12 years, from 2000–2024.

The research results were downloaded from PubMed and then uploaded on the web application "Rayyan" [Ouzzani, M.; Hammady, H.; Fedorowicz, Z.; Elmagarmid, A. Ray-yan-a Web and Mobile App for Systematic Reviews. Syst. Rev. 2016, 5, 210], a website used to screen and analyze articles, specific for writing reviews.

As the first step, duplicates were identified by the web application, Rayyan. After that, authors evaluated duplicates excluding copies. To limit errors and bias, two authors independently screened titles and abstracts and identified articles irrelevant to the review.
Exclusion criteria were:

- Reports including adults, without age distinction.
- Reports dealing with other themes different from the topic of investigation.

Afterward, full texts were retrieved and assessed for eligibility by the screening authors. Finally, following PRISMA guidelines, references not included in the original search but relevant to the review were examined. Disagreements regarding inclusion/exclusion were settled through discussion between the researchers.

Results

The search on the selected database produced n°98 articles and reviews. Documents were analyzed to confirm their relevance and eligibility. No duplications were identified by researchers.

According to PRISMA guidelines, of the identified items, all abstracts were analyzed, 91 records were excluded as irrelevant, and 5 records were excluded as based on adult population.

In conclusion, 2 records were included in the revision [1, 3].

Figure 1 presents the flow chart of the selection process, adapted from PRISMA guidelines. (Fig. 1)

In details, Lonergan et al. found an association between appearance-related social media behaviors and eating disorders in a sample of Australian adolescents. Moreover, investigating the effects of posting selfies, photo investment and photo manipulation, they found a higher risk for eating disorders, mainly among males [3]. Data form Lonergan et al. were in line with former findings from McLean et al., that explored the link between social media use, body perception and eating concerns in grade seven girls, with a mean age of 13 years. Specifically, the Authors found that girls regularly sharing selfies on social media tended to over-evaluate shape, weight, and body dissatisfaction, compared to those not sharing selfies. Moreover, among girls who shared selfies, higher engagement in manipulation was associated with greater body-related and eating concerns [1]. Table 1 summarizes the evidence and summarize the characteristics of studies. (Table 1)

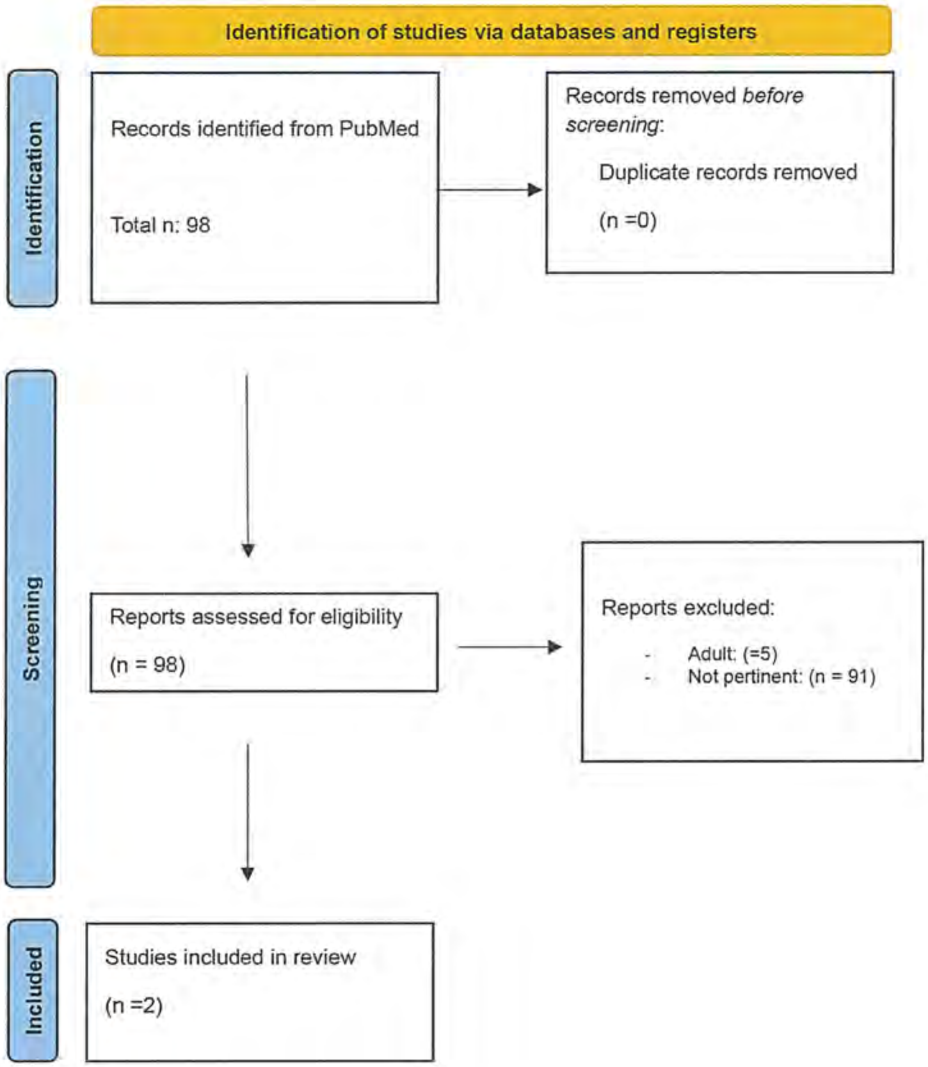

Fig. 1 Flow chart of the selection progress

Table 1 Photo editing and the risk of anorexia

Author	Country	Participants	Age	Main findings
Mc Lean SA, 2015 [1]	Australia	101 females Provenience: 91%Australia, 9% East Asia, Europe, and New Zealand	Mean age 13.3 years	Girls who regularly shared self-images on social media reported significantly higher overvaluation of shape and weight, body dissatisfaction, dietary restraint, and internalization of the thin ideal. Those with a higher engagement in photo manipulation manifested body-related and eating concerns
Lonergan AR, 2020 [3]	Australia	4209 (53.15% female) Provenience: 89.2% Australia, 5.7% Asia, 2.2% Europe, 1.3% Oceania, 0.9% Africa, 0.6% America	Age range: 12–18 years for boys, 11–19 years for girls	Social media behaviours, including photo investment, and photo manipulation correlate to an increased risk of developing eating disorders.

Discussion

Eating disorders are defined as a group of diseases characterized by altered eating behaviors and body image concerns. In adulthood, evidence suggests an association between photo manipulation, body dissatisfaction, and reduced self-esteem. It has also been suggested that photo manipulation could reinforce risks of body shame, depression, and eating disorders [7, 8]. Thus, body image perception represents a key risk factor for the development of eating disorders [9, 10]. Posting edited selfies is

common between minors, with more than 90% of the teens that use social media posting photos of themselves Nevertheless, scientific evidence on the consequences of photo manipulation lacks. Examining the literature, a relationship between disordered eating and body image has been found in adolescent girls with a greater effort in choosing a selfie and monitoring likes/comments. So, photo manipulation with digital editing of a selfie, seems to be linked not only to decreased personal perception, but also to eating concerns. Literature revision provide insight in an association between appearance-related social media behaviors and eating disorders in minors [1, 3].

Photo editing exposes females to greater peer scrutiny of appearance and competition, which, from an evolutionary perspective, has been proposed to increase body dissatisfaction and body concerns. Taking, sharing and comparing selfies through social media, may heighten appearance focus and increase internalization of appearance ideals, contributing to body dissatisfaction. In addition, monitoring of likes/comments on the uploaded selfies may represent an online manifestation of reassurance-seeking [11].

New social media and online chat, including Facebook, Instagram, Snapchat, and TikTok exposure may be associated with lower personal weight satisfaction, higher drive for thinness, and eating disorder symptoms. Studies revealed that time spent on the Internet is significantly related to internalization of the thin ideal, body surveillance, and drive for thinness. In particular, Facebook users scored significantly higher on all body image concern measures than non-users [12]. The more vulnerable the subjects are, the greater the risk is. Young adolescent girls with high levels of body-related and eating concerns might engage in social media activities manipulating selfies to present an ideal appearance when sharing images. In the paper by McLean et al., 20 out of 74 photos had been manipulated. In the selfie-sharing group, higher scores for selfie manipulation were associated with higher scores for body-related and eating concerns [1].

A topic of concern is that social media use among adolescents is increasing, despite the fact that social media access for minors is restricted by age in many countries. In Italy, many platforms, including TikTok, Instagram, Facebook, and YouTube, have age restrictions. However, without a strict parental control, minors can easily access social media platform and download the applications.

Even though social media may help adolescents to build social networks, connect, chat and stay in touch with old and new friends, their use may also be linked to potential harms and unhealthy mental effects, following exposure to inappropriate videos and images, especially in vulnerable categories like adolescents.

A limitation of the study is the few available data connected to few evidences on the pediatric population. Further studies may add important information and improve awareness of this phenomena. Even if our systematic has been based by a detailed strategy adopting PRISMA guideline, we have to declare the risk of selection bias as we limited our review to Pubmed database as is the most extensively used database and search engine in the biomedical and healthcare fields, contain more than 37 million citations and abstracts of biomedical literature. We excluded other datasets, unpublished papers, clinical trial registries, regulatory agency websites, and conference abstracts. Another bias may regard contributing reports focusing on the provenience of the examined population, mainly Australian, and on the different inclusion criteria used by the authors which contribute heterogeneity to the results. Finally, as we got just two findings, no sensitivity analyses have been adopted to compare the reports.

Conclusion and call to action

Although the etiology of anorexia nervosa is not defined and likely multifactorial, exposure to social media may be an important contributor to the onset or worsening of symptoms [13]. Editing tools and image filters may create unrealistic beauty standards and increase the body dissatisfaction in vulnerable adolescents [1, 3]. As demonstrated by a previous survey of the Italian Pediatric Society, eating disorders as well as neuropsychological impairments are increasing among the pediatric population [14]. In order to prevent the risk of a further increase of this group of diseases, the Italian Pediatric Society Communication Group suggests the following action:

- Conducing specific studies on the effect of photo manipulation and sharing edited photo among children and adolescents, to gain evidence specifically target to this population;
- Launch of social campaigns to increase the awareness on photo manipulation risks, in order to prevent neuropsychological effects on minors;
- Providing school education on the use of media devices and social media, underlying risks and benefits of their use and strategies to prevent negative effects;
- Considering the education for a conscious use of technology as part of routine pediatric control visit, especially in the pre-adolescence period;
- Improving parents' awareness on filters and photo editing possible consequences on adolescents' health.

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Author contributions
EB conceived the study; ES coordinated the study; RA and CC participated in its design; TA and RR carried out the literature research. All the authors read and approved the final manuscript.

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Data availability
Not applicable.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
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Competing interests
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Publisher's note

EMPIRICAL ARTICLE

Do You "Like" My Photo? Facebook Use Maintains Eating Disorder Risk

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ABSTRACT

Objective: Social media sites, such as Facebook, merge two factors that influence risk for eating disorders: media and peers. Previous work has identified cross-sectional and temporal associations between Facebook use and disordered eating. This study sought to replicate and extend these findings using an experimental design.

Method: In Study 1, 960 women completed self-report surveys regarding Facebook use and disordered eating. In Study 2, 84 women were randomly assigned to use Facebook or to use an alternate internet site for 20 min.

Results: More frequent Facebook use was associated with greater disordered eating in a cross-sectional survey. Facebook use was associated with the maintenance of weight/shape concerns and state anxiety compared to an alternate internet activity.

Discussion: Facebook use may contribute to disordered eating by maintaining risk for eating pathology. As such, targeting Facebook use may be helpful in intervention and prevention programs. © 2014 Wiley Periodicals, Inc.

Keywords: eating disorders; social media; Facebook; body dissatisfaction; anxiety

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Introduction

With 655 million daily users,[1] Facebook represents a ubiquitous merging of two social influences linked to risk for developing eating disorders through reinforcement of the thin ideal: media and peers (for recent review, see Keel and Forney[2]). Traditional media, such as movies, television, and magazines, portray an unrealistically thin ideal for female beauty.[3–5] Exposure to this ideal leaves many adolescent girls and women with body dissatisfaction,[6–8] which increases risk for disordered eating over time.[9,10] Peers influence risk for body dissatisfaction and eating pathology,[11–13] in part, by endorsing the thin ideal.[13] Today, college students use Facebook an average of 100 min/day, interacting with peers primarily by posting and viewing photos.[14] The ability to post carefully selected photos that may be digitally altered using online tools, such as "Plump & Skinny Booth,"[15] allows Facebook users to present and view images that adhere to unrealistic beauty ideals. Further, social media may reinforce the thin ideal by the posts, "likes," and comments of idealized images. Thus, it is important to understand whether and how the use of this common social media platform may influence risk for eating pathology.

Previous work has established small but significant associations between social media use and thin ideal internalization, body dissatisfaction, and eating pathology. Having a Facebook account was associated with greater thin ideal internalization, body surveillance, and drive for thinness in a large sample of adolescent girls.[16] Among those with Facebook accounts, number of "friends" and time spent on social media were significantly associated with increased body image disturbance.[16] Smith et al.[17] conducted a longitudinal study in college women in which they measured "maladaptive" Facebook use and changes in eating pathology over four weeks. Smith et al.[17] found that maladaptive Facebook use at baseline, defined as the tendency to seek out negative evaluations and/or engage in social comparisons, prospectively predicted greater eating pathology at follow-up. This effect was partially mediated by body dissatisfaction, suggesting that Facebook use may impact eating pathology via body dissatisfaction. Importantly, both maladaptive Facebook use and increases in disordered eating may be caused by an underlying third variable.

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Thus, an experimental design is needed to establish causation.

Study 1 aimed to replicate correlations between greater Facebook use and increased eating pathology.[16] Study 2 examined whether Facebook use causes temporal changes in eating disorder risk factors, specifically weight/shape concerns and anxiety,[18,19] and behavioral manifestation of concerns.[20,21] We hypothesized a positive correlation between higher Facebook use and higher disordered eating and that Facebook use would cause momentary increases in body dissatisfaction, anxiety, and urges to exercise. We focused on state anxiety because of its robust association with eating disorders.[22,23]

Study 1

Participants and Procedure

Nine hundred-sixty female college students completed a large screening instrument for a southeastern state university psychology subject pool in fall ($n = 626$) and spring ($n = 334$) semesters. Participants in the fall were significantly younger (M (SD) = 18.44 (.85) years) than in the spring (M (SD) = 19.10 (1.11) years), $t(958) = 10.34$, $p < .001$, reflecting the passage of time. Across semesters, participants did not differ in ethnicity (18.45% Hispanic, $X^2(1) = .03$, $p = .87$) or race (86.45% White, $X^2(3) = 2.14$, $p = .54$). Participants received course credit. The university's institutional review board approved the study; informed consent was given prior to participation.

Measures

Eating Attitudes Test 26 (EAT-26)[24] assessed disordered eating attitudes and behaviors on a six-point scale from "Always" to "Never." The nonclinical scoring was used to ensure adequate sensitivity to individual differences.[25] Higher scores indicate greater disordered eating. The EAT-26 distinguishes between eating disorder cases and noncases,[26] and exhibits good convergent validity.[27] Due to limited space on the screening instrument, 19 items of the EAT-26 comprising the Dieting and Bulimia/Food Preoccupation subscales were used. Typical items include "I eat diet foods" and "I give too much time and thought to food." We used total scores from these subscales as a global measure of eating pathology, referred to as the EAT-19. Internal consistency of the EAT-19 was .92 in both the fall and the spring.

Duration of Facebook use was assessed with the question "How much time do you spend on Facebook per week?" Response options were 1 = "0 min," 2 = "<30 min," 3 = "30 min to < 1 h," 4 = "1 to <2 h," 5 = "2 to <4 h," 6 = "4–7 h," and 7 = ">7 h."

Results

The vast majority of women endorsed using Facebook on at least a weekly basis (97% in fall and 95.5% in spring). Mean (SD) scores for duration of Facebook use were 4.58 (1.52) in the fall and 4.74 (1.57) in the spring, reflecting approximately 2 h of Facebook use each week, with no significant difference in use between semesters, $t(958) = 1.53$, $p = .13$. A small but significant positive correlation was observed between duration of Facebook use and disordered eating for participants in fall, $r(623) = .11$, $p < .01$, and spring, $r(334) = .16$, $p < .01$.

Study 2

Participants

Women ($N = 84$) included in Study 1 who endorsed Facebook use on a weekly basis (Facebook use ≥ 2) were recruited to participate in Study 2. Sociodemographic variables did not differ significantly between Study 1 and Study 2 participants. Participants identified as Caucasian (77.4%; $n = 65$), Hispanic (15.5%; $n = 13$), and African-American (7.1%, $n = 6$) and reported a mean (SD) age of 18.39 (.69) years. To ensure an adequate range of disordered eating, we used an enriched sampling design that balanced representation of individuals with low, medium, and high EAT-19 scores from Study 1 screens. Stratified randomization to the experimental and control groups was used to match disordered eating levels between conditions. EAT-26 scores from Study 2 did not differ between those randomly assigned to the experimental condition ($M = 63.81$; $SD = 20.57$) and the control condition ($M = 63.25$; $SD = 18.81$), $t(81) = -.13$, $p = .90$.

Procedure

After providing informed consent, participants completed a demographic survey, Visual Analog Scales (VASs; described below), and the State Trait Anxiety Inventory (STAI) State scale. Participants in the experimental group were instructed to log onto their Facebook account and spend 20 min on the site. Participants in the control group were instructed to use the internet for 20 min on Wikipedia researching the ocelot, a neutral rainforest animal, and on YouTube watching a preselected ocelot video. The control condition was designed to match the experimental condition on exposure to

text versus images while eliminating any images related to the human body. Participants were asked to remain on the assigned website(s) and not to use any links to connect to other sites to minimize risk of viral infections. This ensured that participants spent the entire 20 min in their assigned condition rather than connecting to another website. Participants were instructed to otherwise use the sites as they normally would. After 20 min of internet use, participants completed a second questionnaire packet, consisting of VAS, a STAI State scale, questions regarding their Facebook use, and the EAT-26 (described subsequently). Following internet use, the researcher cleared Internet browser history while the participant watched to ensure confidentiality of participants' personal information and compliance with study procedures. Upon completion, participants were debriefed and given class credit. The university's institutional review board approved this study.

Measures

Demographic information was collected with a brief survey that included questions about age, race, and ethnicity.

VAS ratings measured momentary experiences by having participants their level of "preoccupation with weight," "preoccupation with shape," and "urge to exercise," "RIGHT NOW" by placing a vertical line on a 100 mm horizontal line, anchored from "None at all" to "Extremely." The VAS is more sensitive to changes than Likert-type scale responses, as the latter may be influenced by recall of baseline answers.[28] Additional items probed for more serious disordered eating urges (e.g., "urge to vomit"). However, due to the small sample size and low base rate of these behaviors in a nonclinical sample, variance was too low to permit meaningful analyses. Preliminary analyses demonstrated significant robust correlations between responses on the VAS scales of "preoccupation with weight" and "preoccupation with shape" (Time 1 $r(75) = .89$, $p < .001$; Time 2 $r(75) = .95$, $p < .001$). Thus, these VAS items were averaged into a single "preoccupation with weight/shape" variable at Time 1 and Time 2 for analyses. VAS have successfully been used in other experimental studies examining changes in mood and body image over similar time frames.[29–31]

Eating Attitudes Test. In Study 2, participants completed the full EAT-26.[24] Test–retest reliability from the 19 items administered in Study 1 and Study 2 was high, $r(83) = .90$, $p < .001$. Cronbach's alpha for the EAT-26 was .91 in Study 2.

State Trait Anxiety Inventory. The STAI State subscale measured current anxiety before and after internet use.[32] This questionnaire assesses responses to questions such as "I feel nervous" on a four-point scale ranging from "almost never" to "almost always." Internal consistency was high (Time 1 $\alpha = .92$; Time 2 $\alpha = .93$).

Facebook survey questions were developed to understand the amount of time spent using Facebook, participants' activities on Facebook (e.g., viewing photos of friends, posting updates), importance of Facebook features (e.g., receiving comments or "likes" on their photos and posts), and access to Facebook (e.g., via a smartphone). Survey items are included in the Appendix. For participants assigned to the Facebook condition, an additional question evaluated how similar the 20 min of use was to their typical use of Facebook, with responses on a five-point scale ranging from "Not at all" to "Completely." Participants in the experimental condition indicated that their Facebook use was "Moderately" to "Very" representative of their typical use ($M = 3.52$; $SD = 1.19$). To evaluate how participants used Facebook, items were analyzed individually, and a Facebook score was created from Items 9, 10, 11, 12, 13, 14, 16, and 17. Facebook score reflects the importance and frequency of using Facebook features posited to heighten weight/shape concerns. Internal consistency of the Facebook score was good, $\alpha = .85$.

Data Analyses

Correlations examined the association between disordered eating and both Facebook items and Facebook score. Repeated measures analysis of variance assessed the effect of experimentally manipulated Facebook use as a between-subjects variable on within-subject changes in momentary ratings of "preoccupation with weight/shape," state anxiety, and "urge to exercise." Significant group × time interaction effects were followed by post hoc comparisons.

Results

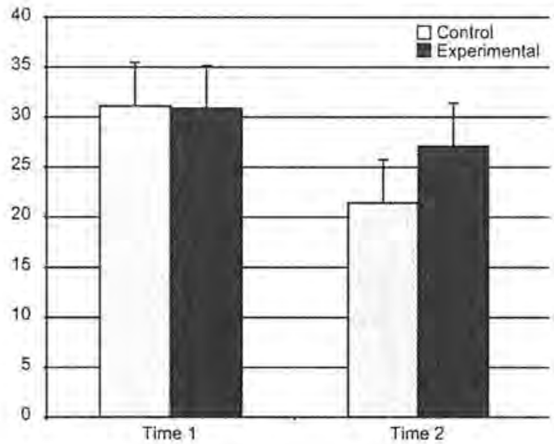
In Study 2, a similar effect size was found for the association between time spent on Facebook and EAT-26 score; however, due to the smaller sample size of Study 2, this association was not statistically significant, $r(83) = .09$, $p = .44$. Among the 84 participants in Study 2, mean (SD) time reported per Facebook session was 20.06 (17.75) min, while mean (SD) total time per day on the site was 76.28 (68.70) min. Most participants used Facebook daily ($M = 6.46$; $SD = 1.22$). The majority (91.7%; $n =$

TABLE 1. Effect of Facebook use on momentary disordered eating attitudes and feelings

VAS Scale	Group Mean (SE)	Pre Mean (SE)	Post Mean (SE)	Group $F(1,73)$	Time $F(1,73)$	Group × Time $F(1,73)$
Weight/shape preoccupation		31.01(2.97)	24.27 (3.01)	.22	23.62[a]	4.52[b]
Control	26.28 (4.14)	31.12 (4.23)	21.43 (4.29)			
Experimental	29.00 (4.09)	30.90 (4.17)	27.11 (4.23)			
STAI state anxiety[c]		34.99 (1.09)	34.87 (1.20)	1.50	0.05	7.55[d]
Control	36.29 (1.59)	37.08 (1.56)	35.50 (1.72)			
Experimental	33.57 (1.55)	32.90 (1.52)	34.24 (1.67)			
Urge to exercise		36.42 (3.33)	31.85 (3.27)	0.55	15.48[a]	0.002
Control	31.72 (4.63)	34.03 (4.75)	29.41 (4.66)			
Experimental	36.55 (4.57)	38.82 (4.68)	34.29 (4.59)			

[a] $p < .001$.
[b] $p < .05$.
[c] $df = 1, 72$.
[d] $p < .01$.

FIGURE 1 Visual analogue scale ratings of weight/shape concerns before and after internet use. Error bars represented standard errors of the mean.



77) of participants endorsed having a smart phone; 94.8% (n = 73) of those with a smartphone endorsed using a Facebook application. Among Facebook activities, 66.7% (n = 56) answered that they choose to look at photos over other activities.

EAT-26 scores were significantly associated with scores on several of the individual Facebook items used to create the Facebook score. Participants with greater disordered eating endorsed greater importance of receiving comments on their status ($r(83) = .32$, $p < .01$) and photos ($r(83) = .29$, $p = .01$), and greater importance of receiving "likes" on their status ($r(83) = .29$, $p < .01$). Those with greater eating pathology reported untagging photos of themselves more often ($r(83) = .34$, $p = < .01$) and endorsed comparing their photos to their female friends' photos more often ($r(83) = .22$, $p = .04$). Disordered eating was not associated with the importance of "likes" on photos ($r(83) = .16$, $p = .16$), nor with the frequency of changing profile pictures ($r(83) = -.15$, $p = .18$). Consistent with study hypotheses, those with the greatest disordered eating had higher Facebook scores, $r(83) = .38$, $p < .001$.

To understand the causal effects of Facebook use, comparisons were made between the experimental and control condition over time in weight/shape concerns, state anxiety, and urge to exercise (see **Table 1**). Participants in both conditions endorsed a decrease in their preoccupation with weight and shape from immediately before to immediately after spending 20 min on the internet, $p < .001$, $d = .30$. A significant group by time interaction ($p = .04$) indicates that the effect of time depended upon condition. Specifically, participants in the control group demonstrated a greater decline in weight/shape preoccupation than did participants who spent 20 min on Facebook. Post hoc comparisons supported a significant decrease in weight/shape preoccupation in controls ($F(1,36) = 21.29$, $p < .001$, $d = .42$) and a less robust decline in experimental participants ($F(1,37) = 4.34$, $p = .04$, $d = .13$). Weight/shape preoccupation did not significantly differ between conditions at Time 1 ($F(1,73) = .001$, $p = .97$, $d = .01$) or Time 2 ($F(1,73) = .86$, $p = .35$, $d = -.22$). The significant interaction effect remained after controlling for EAT-26 scores, suggesting that Facebook use maintains a preoccupation with weight and shape compared to an internet control condition (see **Fig. 1**).

Across conditions, state anxiety was maintained over time ($p = .82$). However, the effect of time varied by condition ($p < .01$). Specifically, participants in the control condition endorsed a significant decrease in anxiety ($F(1,35) = 6.04$, $p = .02$, $d = .56$) while participants in the experimental condition endorsed a nonsignificant increase in anxiety ($F(1,37) = 2.57$, $p = .12$, $d = -.13$). Post hoc comparisons supported no significant differences between experimental and control participants at Time 1 ($F(1,72) = 3.72$, $p = .06$, $d = .44$) or at Time 2 ($F(1,72) = .28$, $p = .60$, $d = .12$). The significant interaction effect, which remained once controlling

for EAT-26 scores, suggests that Facebook use maintains state anxiety compared to an alternative internet activity.

Urge to exercise decreased after spending 20 min on the Internet ($p < .001$, $d = .26$). The effect of time did not depend on condition ($p = .46$), suggesting that general internet use, not Facebook use specifically, is associated with the decrease.

Discussion

Before the advent of social media sites, women were confronted with unrealistically thin images of beauty from magazines, films, and television. Women also engaged with peers who represented a full range of expected body weights and shapes in their immediate environment, but could reinforce the thin ideal through discussions and behaviors. Now, women have a constant and active space to engage in social comparison with peers who may simultaneously portray and reinforce the thin ideal. Replicating previous research,[16] we found a significant but small association between Facebook use and disordered eating levels in two large samples of college-aged women. In addition, how women use Facebook (reflected by higher Facebook score) was associated with greater disordered eating. While previous longitudinal findings[17] reinforce that maladaptive patterns of Facebook use precede increases in disordered eating, our experimental design indicates that typical Facebook use may contribute to maintenance of weight/shape concerns and state anxiety, both of which are established eating disorder risk factors.[18,19] To the extent that these effects could be discerned after only 20 min of typical Facebook use in a laboratory setting raises concerns about how use of the site throughout the day may impact eating disorder risk.

Of interest, in our experimental design, internet use, regardless of condition, was associated with decreases in weight and shape preoccupation and urge to exercise. Such state changes may negatively reinforce internet use, explaining the widespread use of the internet for entertainment. Facebook users may not be aware of this cost because the overall experience may be positive. Without a non-internet control condition, it is unclear whether the observed main effects are specifically due to internet use or the passage of time more generally. Therefore, future research should seek to replicate these effects using a noninternet control condition.

Women with greater eating pathology not only reported spending more time on Facebook in Study 1, but also reported engaging in appearance-focused behaviors, such as comparing their appearance to friends' pictures and untagging photographs of themselves, perhaps in order to remove unflattering photographs and minimize opportunities to become the target of downward social comparison. In line with self-reported behaviors on Facebook, those who placed greater importance on the responses elicited by their Facebook content reported greater eating pathology. Specific aspects of use (e.g., social comparison to photos of peers) should be examined as potential mediators of the relationship between Facebook use and the maintenance of eating disorder risk. Alternatively, tendencies toward social comparison may serve as a moderator of the influence of Facebook use on eating disorder risk. Replication in larger samples would help to untangle these potential associations between individual and social risk factors.

Pending replication of these and other findings,[17] Facebook could be targeted as a maintenance factor in prevention programs. For example, interventions could address the implications of appearance-focused comments such as "you look so thin" or "I wish I had your abs," in perpetuating the thin ideal on Facebook, much as "fat talk" perpetuates this ideal in everyday conversations. An adaption of the "Fat Talk Free" campaign[33] as well as adaptations of media literacy programs[34,35] could encourage girls and women in the responsible use of social media sites. Similarly, if research finds that photoenhancing technology is common, advocacy may be effective in reducing the use of photoenhancing technology to promote unrealistic ideals.

The current studies benefited from a large college sample and measures with good psychometric properties. Our sampling approach ensured a range of disordered eating levels, allowing greater generalizability. Participants were representative of other college samples studied, as evidenced by comparable estimates of reported time on Facebook.[14] However, results should be interpreted with limitations in mind. We cannot rule out the possibility that our results reflect demand characteristics. Importantly, such effects should have prevented our observation that Facebook use was associated with decreases in both weight/shape concerns and urges to exercise, suggesting that changes (or the lack thereof) did not represent participants' efforts to unconsciously support our hypotheses. However, the opposite may be true; our findings may underestimate the effect of Facebook use on maintaining weight/shape concerns. Our control condition allows inferences about Facebook use compared to one other internet activity and may not generalize to other activities.

Specifically, the interaction effects observed in this study were driven, in part, by an observed decrease in weight and shape concerns in the control condition. This decrease over time may not be observed in naturalistic environments. An ecological momentary design[36] may better capture natural changes in affect as well as weight and shape preoccupation in relation to Facebook use. Our study does not address whether Facebook use influences eating disorder risk above and beyond other social or media influences. Future research should compare face-to-face social interaction to Facebook use. Additionally, the use of interviews about eating and Facebook use in future research would enhance understanding of the observed associations. As we measured momentary changes in risk factors, our results do not address whether Facebook use may contribute to actual eating disorders. However, the maintenance of risk is important to identify for prevention efforts.

Advances in technology may be impacting the nature of risk factors for disordered eating pathology in women. While the overall use of Facebook has a small but significant association with disordered eating, specific aspects of use demonstrate more robust associations with disordered eating. In addition, we found evidence that Facebook use may maintain preoccupation of weight and shape and state anxiety, both well-replicated risk factors for eating pathology. Future longitudinal research using ecological momentary assessment[36] in both at-risk and eating disordered populations would allow better understanding of the effects of Facebook use over time in a natural setting. As technology continues to change, more research is needed to understand the effects of social media in maintaining risk for eating disorders and other psychological problems.

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Appendix

Facebook Questions

1. What is the average amount of time you spend on Facebook for each session? ________
2. How much overall time do you spend on Facebook each day? ________
3. How many days a week do you use Facebook? ________
4. Do you have a smart phone? Y N
   If so, do you use the Facebook application? Y N
5. If you were asked to use your Facebook in the lab, how representative was the session just now of how you normally use Facebook?
   1) Not at all
   2) Somewhat
   3) Moderately
   4) Very
   5) Completely
6. When using Facebook, which do you do the most? (Rank from 1-13, where 1 is the HIGHEST and 13 is the LOWEST.)
   1) Look at photos _____
   2) Comment on or "like" status updates _____
   3) Comment on or "like" friend's photos _____
   4) Use notes _____
   5) Use events _____
   6) Use chat or send messages _____
   7) Post your own photos _____
   8) Post your own status updates _____
   9) Find friends _____
   10) Look at business/company pages _____
   11) Use apps and games _____
   12) Use check-ins _____
   13) View or post in groups _____
7. On Facebook, what do you find to be the most interesting if you had to choose **only one**? (Please circle only one.)
   1) Look at photos
   2) Comment on or "like" status updates
   3) Comment on or "like" friend's photos
   4) Use notes
   5) Use events
   6) Use chat or send messages
   7) Post your own photos
   8) Post your own status updates
   9) Find friends
   10) Look at business/company pages
   11) Use apps and games
   12) Use check-ins
   13) View or post in groups
8. If you were asked to use your Facebook in the lab, how long ago did you use Facebook before this session? ________
9. How often do you compare your photos to photos of your female friends?
   1) Never
   2) Rarely
   3) Sometimes
   4) Usually
   5) Always
10. How important is it to you to have more likes or comments on your photos than your other female friends?
    1) Not at all
    2) Somewhat
    3) Moderately
    4) Very
    5) Extremely
11. How important is it to you that people "like" your photos?
    1) Not at all
    2) Somewhat
    3) Moderately
    4) Very
    5) Extremely
12. How important is it to you that people "like" your status updates?
    1) Not at all
    2) Somewhat
    3) Moderately
    4) Very
    5) Extremely
13. How important is it to you that people comment on your photos?
    1) Not at all
    2) Somewhat
    3) Moderately
    4) Very
    5) Extremely
14. How important is it to you that people comment on your status updates?
    1) Not at all
    2) Somewhat
    3) Moderately

4) Very
5) Extremely

15. How often do you change your profile picture?
    1) Never
    2) Once every 3 months
    3) Once a month
    4) Twice a month
    5) Once a week
    6) More than once per week
    7) Daily
16. How often do you take photos in public for the main purpose of posting them on Facebook?
    1) Never
    2) Rarely
    3) Sometimes
    4) Usually
    5) Always
17. How often do you untag your photos?
    1) Never
    2) Rarely
    3) Sometimes
    4) Usually
    5) Always
18. Why do you untag your photos?
    1) Unflattering
    2) Inappropriate for family/coworkers
    3) Not representative of who I am/what I am really like
    4) No longer dating person in photo
    5) No longer friends with person in photo
    6) Other (please specify: ____________________)

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Digitally curated beauty: The impact of slimming beauty filters on body image, weight loss desire, self-objectification, and anti-fat attitudes

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ABSTRACT

The use of Augmented Reality (AR) beauty filters has been on the rise, given the advancement of technology making them more easily accessible, plentiful, and realistic. Although previous work has established beauty filters as a source of poor body image, little is known about the mechanisms for these outcomes. The current study applies social comparison theorizing to the use of beauty filters and establishes a new concept in the field: social self-comparison (i.e., the process of individuals making comparisons between their filtered image and real self-image). An online experiment of social media users ($N = 187$) was conducted to examine the effects of using a slimming beauty filter on body image and weight-related perceptions. Results indicate that comparison processes were strongest when participants used the beauty filter on their own image versus viewing someone else's filtered image, supporting the importance of examining social self-comparison processing. Overall, the results of the current study underscore the impact of beauty filter usage on body image, identifying body dysmorphia and social self-comparison as important mediators in the relationships between filter usage and body image-related outcomes, including a desire for weight loss, self-objectification, and anti-fat attitudes, among others.

Beauty filters have risen in availability and popularity, and with this rise have emerged concerns about the effects of filter use on mental health and the internalization of unrealistic beauty standards (Alsaggaf, 2021; Moreschi & Aaron, 2024). Social media filters use digital effects to modify photos and videos, and augmented reality (AR) beauty filters are specifically designed to enhance a person's appearance and attractiveness. They heighten the user's level of attractiveness by adding make-up, heightening cheekbones, or slimming and changing the proportions of one's face. Social media can be a place of connection and fun but also a source of comparison and pressure to showcase an idealized version of the self (Verrastro et al., 2020; Vogel et al., 2014). As social media further encourages users to compare themselves with others and showcase an idealized version of the self, beauty filters may exacerbate negative outcomes on body perceptions.

Existing research highlights the negative influence of social media on social comparison and body image (Fardouly et al., 2015; Jiang & Ngien, 2020; Tiggemann & Anderberg, 2020). Using beauty filters extends the potential for social comparison with others to compare yourself to an idealized online version. Research suggests that taking and editing or manipulating selfies is more harmful to self-image than simply posting selfies (Vandenbosch et al., 2022). This suggests that the process of using digital techniques to enhance one's image may have a negative influence on body perceptions. We argue that using beauty filters fosters a new form of social comparison – *social self-comparison.*

We define social self-comparison as comparing oneself to a digitally enhanced version of oneself, typically altered through a social media filter. The "social" in social self-comparison derives from the use of a digital tool that is collectively endorsed through social media platforms and utilized to present an image of the self to others online. As users begin seeing themselves in new ways through beauty filters, they may compare their real appearance to these mediated versions of the self. In this way, using beauty filters may make users prefer their filtered image over their real-life appearance. Beauty filter use has potentially severe implications as filters may influence some users to feel poorly about their bodies and engage in unhealthy cognitions and physical practices to change their appearance (Javornik et al., 2022; Beos et al., 2021; Sun, 2021). As social media filter use and technology continue to grow and become more realistic, the problem arises with what these filters communicate to users about societal expectations for what a person can (and should) look like. MIT Technology Review reports that around 200 million daily users use AR filters on Snapchat, and around 600 million have used an AR filter on Facebook or Instagram (Ryan-Mosley, 2021).

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In sum, AR filters are widespread and their use rampant. Coupled with the negative impacts of their usage, it is clear that the ability of AR filters to induce social self-comparison is worth exploration, including in how this phenomenon deepens the effects of traditional social comparison.

Our research examines the effects of beauty filters on social comparison, social self-comparison, and various body-related outcomes. Participants were randomly assigned to one of three conditions: using a beauty filter (one that slims the face), watching someone else use a beauty filter, or using a filter that simply changed the color of one's photo (i.e., adding a blue film over the image). We hypothesized that using a beauty filter would result in higher levels of body dysmorphia, body ideal discrepancy, desire for weight loss, self-objectification, anti-fat attitudes, and a preference for the filtered image, mediated by comparison processes and body dysmorphia. This study utilized an experimental design to examine group differences for these outcomes based on the type of filter used, with the slimming beauty filter predicted to foster heightened negative cognitions about one's body in comparison to the other filter conditions. Social self-comparison and body dysmorphia emerged as critical factors in understanding the negative impacts of filter usage. The findings highlight the detrimental effects of AR beauty filters on body image, emphasizing the need for awareness of the potential outcomes of using such digital tools. The results of this research also advance social comparison theorizing in the age of social media.

1. Literature review

1.1. *Social comparison and social media*

Social comparison theory is a psychological framework from which to understand how the process of comparing ourselves to others helps us to better understand ourselves and our traits, such as attractiveness (Myers & Crowther, 2009). In other words, human beings make comparisons to others as a means of self-assessment. There are various ways in which social comparison theorizing has expanded over the years, including how we conceptualize and measure state-level and trait-level social comparison. State-level comparisons are those that are prompted or triggered by salient others, stimuli, and situations. For example, this may include someone reacting to an advertisement featuring a thin, stereotypically attractive model in which they then consider how their body compares (Tiggemann & McGill, 2004). Alternatively, one may just be higher in social comparison orientation, or trait-level social comparison, which is one's general propensity to make comparisons to others (Gibbons & Buunk, 1999).

When using Instagram and other social media platforms, users may engage in upward comparison by comparing themselves to someone perceived to be better off in some way (in this case, based on the appearance of their body), leading to a drive for thinness, body dissatisfaction, body surveillance, and other appearance-related concerns (Seekis et al., 2020). These comparisons may also negatively impact health, including prompting disordered eating (e.g., Saunders & Eaton, 2018). Traditionally, upward comparisons on social media have been made with others on those platforms, such as models (e.g., Tiggemann & McGill, 2004), celebrities, and friends (e.g., Ho et al., 2016). Social media posts guised in the context of "fitness" and "health" content have also been demonstrated to increase social comparison and negative body image for women, as cumulative exposure to these posts exposes users to a slim, idealized version of a fit body (Lewallen & Behm-Morawitz, 2016). However, with the advancement of social media has also come the advancement of other related technologies available on these platforms, such as augmented reality (AR) beauty filters.

1.2. *Filter usage and body image*

Through filters, users can rapidly and efficiently picture themselves in new, digitally altered ways, given the advancement of AR technologies – with a different head shape, eye color, and even facial structure, size, and features. It is no secret in body image research that exposure to manipulated/retouched photos can hurt the body image of viewers – this becomes even stronger for users high in social comparison tendencies (Kleemans et al., 2018). One review of the literature found that most studies in this domain show a positive relationship between photo editing and body concerns as well as related outcomes, such as self-objectification, body shame, and overvaluation of weight (McGovern et al., 2022).

Even more importantly, filters and photo editing allow users to see themselves in ways they may even find preferential to their current, real selves. This ability comes with serious implications. For example, high-frequency users of filters on Instagram are more likely to engage in social appearance comparison and internalize general attractiveness ideals (Mancin et al., 2024). This draw to filters may stem from a desire for idealized self-presentation, as filters allow users to "fix" their insecurities, like blurring a pimple or whitening teeth (Javornik et al., 2022). As people begin to see themselves more desirably, they may begin to wish for those changes permanently. Therefore, it is no surprise that the use of filters and photo editing has been linked to greater acceptance of cosmetic surgery as well as greater intentions to have cosmetic surgery (Beos et al., 2021; Sun, 2021).

1.3. *Expanding social comparison theory*

1.3.1. *Social self-comparison*

We extend social comparison theorizing to examine the comparative processes users may engage in when viewing their images altered by AR beauty filters. Specifically, users may compare themselves to a "better" version of themselves – their filtered image. As explained earlier, we conceptualize this as social self-comparison – comparing oneself to a digitally enhanced version, typically altered through an AR social media filter for images or videos. Research shows that typical upward comparisons to models, peers, and other people can result in negative body image (e.g., Seekis et al., 2020). Therefore, one may expect that making comparisons to a closer object (in this case, an idealized version of oneself) will also result in a comparative cognitive process that produces negative body perceptions. Social self-comparison provides researchers a lens through which they can study the influence of filters, selfies, and social media documentation of the self on perceptions of the self. The process is inherently social in nature, given the communal use of filters, the public or semi-public nature of social media, and the sharing of social media content.

In short, social self-comparison is a new theorizing about comparison, highlighting that the object of comparison can be a digitally altered version of the self. This may be especially important in the context of how users feel about their bodies and view them, as each type of comparison may serve as a mechanism for other negative outcomes. This may include exaggerating the gap between users' current weight and how they wish to look (body ideal discrepancy) as well as their desire to lose weight. Specifically, in the case of this study, state-level social comparison will increase after exposure to someone else using a beauty filter, leading to these outcomes. Similarly, the same process will happen as other participants use a beauty filter. However, this indirect effect will be much weaker in the case of using a filter that does not change a person's appearance to be more socially desirable.

How much participants view themselves as an object and value their own sexual appeal, known as self-objectification (Fredrickson & Roberts, 1997), may also be impacted by beauty filters. Self-objectification is about seeing oneself from a third-person perspective, placing looks above ability and feelings in importance. In short, what matters to our self-concept is the perception of how others view their bodies in terms of sexual appeal and attractiveness. Therefore, a consequence of self-objectification is body surveillance, or the constant thinking about and monitoring of one's appearance. Additionally, self-objectification can result in the experience of body shame, appearance anxiety, a "diminished awareness of internal bodily states" like being able to

identify hunger and emotions, as well as "reduced concentration" on "mental and physical tasks" (Calogero, 2012, p. 575). In instances where self-objectification is heightened, like during a college student organization recruitment event or while trying on clothes, people may also engage in disordered eating, experience increased sexual dysfunction, body shame, and even worse performance in school (Rolnik et al., 2010; see Daniels et al., 2020 for a review; see Moradi & Huang, 2008 for a review). Given this, self-objectification can operate as a trait, but also may occur in moments where the body and its appearance is centered (Calogero, 2012). In this way, self-objectification can be triggered, in this case by making comparisons to filtered social media images.

Additionally, the use of beauty filters and comparison processes may lead to negative views about fatness, or anti-fat attitudes. Anti-fat attitudes are rooted in fatphobia, which is "a pathological fear of fatness often manifested as negative attitude and stereotypes about fat people" (Robinson et al., 1993, p. 468). Fatphobia is pervasive in society, both in one's view of the self and others. In one study, women were asked to imagine gaining 100 pounds said they would consider moving away or even suicide (Fahs & Swank, 2017). In another study, nearly half of respondents reported that they'd be willing to give up one year of their life rather than be obese. Some respondents also indicated they'd be willing to give up 10 or more years of life (15%), lose the ability to have children (25%), or get divorced (30%) (Schwartz et al., 2006). This provides a clear indication of just how deeply rooted fatphobia is within US society, as it is avoided at devastatingly large costs.

In using filters, individuals can see themselves in ways that uphold societal standards for beauty, including thinness. Users may seek or desire permanent cosmetic changes as they begin to picture themselves in these new ways (Beos et al., 2021; Sun, 2021). In turn, they may begin to develop a dislike of their current appearance. In the case of beauty filters, the filtered image and one's real appearance may result in a greater dislike of their excess weight. Therefore, they may experience greater anti-fat attitudes and a preference for the filtered image. Given the aforementioned information, we propose the following.

Hypothesis 1. Condition will predict social comparison, such that those using a beauty filter will experience the greatest level of comparison followed by those watching someone else use a beauty filter and the control condition.

Hypothesis 2. State comparison will mediate the relationship between condition and a) body ideal discrepancy, b) desire for weight loss, c) self-objectification, d) anti-fat attitudes, and e) preference for filtered image.

See Fig. 1 for a pictorial representation of Hypothesis 2 predicted mediation relationships. Greater levels of state comparison will foster greater levels of the outcome variables.

1.3.2. Body dysmorphia

Body dysmorphia, or one's perception of their body as being flawed beyond what an objective outsider may see, is well-established as being a predictor of disordered eating and exercise behavior and self-criticism (Alsaidan et al., 2020; Matos et al., 2023). Symptoms of body dysmorphia include increased body consciousness, shame, guilt, and perceived body surveillance (Foroughi et al., 2019; du Rocher et al., 2023). For those experiencing body dysmorphia, they may feel embarrassed about their bodies and, therefore, avoid social situations and engage in disordered eating (Rizwan et al., 2022). Body dysmorphia may have additional serious implications for physical and mental health, as body dysmorphic disorder has been linked to cosmetic surgeries and even self-mutilation to be approved for otherwise healthy limb removal in extreme cases (Chan et al., 2011). Social media has been linked to body dysmorphia in that social media use may lead to an increase in dysmorphia and related outcomes, such as poor self-esteem and anxiety (Rizwan et al., 2022; Raj et al., 2022). This includes the use of filters and other photo editing online.

Beauty filter usage may increase body dysmorphic cognitions, as seeing an idealized version of others and themselves may make individuals feel negatively about their real-life looks. Given the connection between body dysmorphia and a desire to change one's appearance (Rizwan et al., 2022; Chan et al., 2011), filter users may feel unsatisfied with their current selves after filter use, and wish to make an appearance change. In short, using a beauty filter or watching someone else use a beauty filter may trigger someone to feel unreasonably poorly or anxious about their current body (i.e., body dysmorphic thoughts). Although short-term social media filter exposure may not elicit change in body dysmorphic behaviors, it may trigger body dysmorphic thoughts. Over time, body dysmorphic cognitions may result in disordered behavior. As such, we examine the relationship between social media filter exposure on short-term body dysmorphic cognitions. Due to heightened surveillance of the body and feeling poorly about their current appearance, individuals' desire for weight loss, feeling disgust toward fatness, and the like, are predicted to increase. These effects are expected to emerge most strongly for condition 1 where participants are using the slimming beauty filter on an image of themselves.

Hypothesis 3. Condition will predict body dysmorphic cognitions, such that those using a beauty filter will experience the greatest level of body dysmorphia followed by those watching someone else use a beauty filter and the control condition.

Hypothesis 4. Body dysmorphic cognitions will mediate the relationship between condition and a) body ideal discrepancy, b) desire for weight loss, c) self-objectification, d) anti-fat attitudes, and e) preference for filtered image.

See Fig. 2 for a pictorial representation of Hypothesis 4 predicted mediation relationships. Greater levels of body dysmorphic cognitions will foster greater levels of the outcome variables.

2. Method

2.1. Procedure and participants

An online experiment examined the effects of a beauty filter on body image-related outcomes. Our experiment consisted of three conditions (see Table 1) via random assignment: condition one tasked participants with using a filter that slimmed their face ($n = 63$); condition two consisted of participants watching someone else use a beauty filter, but not using it themselves ($n = 79$); and the third condition required participants to use a neutral filter unrelated to body size/shape. This filter changed the color of their screen/image to blue ($n = 45$). The last condition served as a control condition.

Participants were recruited via ResearchMatch, a non-profit recruitment service consisting of volunteer participants for health-

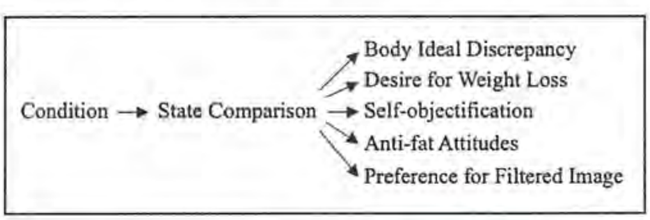

Fig. 1. Pictorial representation of Hypothesis 2.

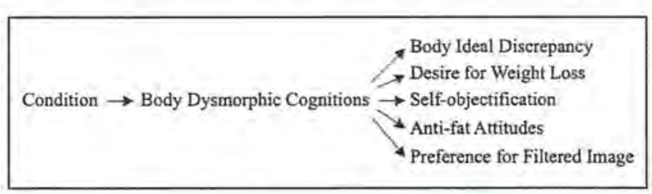

Fig. 2. Pictorial representation of Hypothesis 4.

Table 1
Descriptions of experimental conditions.

Condition	Description
1	Participants used a slim beauty filter on image of self
2	Participants watched a video of a person using a slim beauty filter
3	Participants used a color filter on image of self

related studies in the United States. The service is funded by the National Institutes of Health (NIH). We limited our recruitment to English-speaking adults, primarily under the age of 50, to best reflect the demographic most familiarized and connected to the use of social media filters. Upon recruitment and consent to participate in the study, participants were asked to answer questions regarding their social media consumption and their perceived body size. Afterward, they were given detailed instructions to download the free app, Snow, where they were then tasked with using a specific filter, depending on their condition. This app was chosen due to its ease of accessibility given its cost-free access, as well as its widespread use, as the company reports hosting over 200 million users. We believe that their offerings were representative of filters across social media platforms. Additionally, the app has a large selection of filters, allowing for both a slimming filter and neutral filter – both of which were needed for the study.

Participants in Condition 1 were instructed to use the same beauty filter; participants in Condition 2 were shown a video of someone using the same beauty filter, but did not use it themselves; and in the third condition, participants were instructed to use the color-changing filter. In the condition directions, participants were given screenshots of each step, including the filter to select. The full instructions for each condition are available in the Supplemental Appendix. After condition exposure, participants completed all other measures used in the study's analysis.

The study's true purpose was disguised by the use of general language in the consent form about the study's aims, as well as including distractor items such as health efficacy measures in the questionnaire. We also employed neutral language in our measures to avoid prompting a social desirability bias from participants.

As a data quality check, all participants who indicated that they used other filters (beyond the one they were instructed to use, $n = 4$) during the study were removed from the analysis, as well as those who did not complete the survey, leaving a final sample of $N = 187$. The majority of the participants were white ($n = 153$), followed by Black ($n = 12$), with the remaining participants identifying as another race or as multiple races. The sample consisted of a majority women ($n = 156$), followed by men ($n = 16$), trans women ($n = 13$), and trans men ($n = 2$). The age of participants ranged from 19 to 66 years old ($M = 36.28$, median = 35, $SD = 10.12$).

2.2. *Measures*

2.2.1. *Body ideal discrepancy*

Using images adapted from Skunkard et al. (1983), to measure body ideal discrepancy we first showed them illustrations of nine body size types, ranging from the (1) smallest body to the (9) largest. We asked participants to identify their current perceived body size before using the filter, and then the body size they would prefer to have after using the filter. From these responses, we subtracted the score of one's ideal body from their current perceived body size score. The resulting value is what we conceptualized as body ideal discrepancy, as we were interested in determining how different their current body is from the body they wish they had ($M = 1.4$, $SD = 1.37$).

2.2.2. *Body dysmorphic cognitions*

To capture participants' body dysmorphia, we utilized six items from the cognitions subscale of the Body Dysmorphia Scale (BDD-SS) (Wilheim et al., 2016). The cognitions subscale measures the internal dialogue one may have regarding concerns over their appearance. These cognitions, more so than symptomatic behaviors of body dysmorphia (e.g., exercising excessively, avoiding mirrors), may become salient after using a slimming filter. Items included "If I could look just the way I wish, I would be much happier" and "If my appearance is defective, I will end up alone and isolated." Responses ranged from (1) strongly disagree to (7) strongly agree ($M = 3.4$, $SD = 1.27$, $\alpha = 0.82$). Higher response scores represent a higher occurrence of body dysmorphia in participants.

2.2.3. *Desire for weight loss*

In order to evaluate participants' desire for weight loss, we presented three items: "I would like to lose weight," "I am happy with my current weight" (reverse-coded), and "It is my goal to lose weight." Responses ranged from (1) strongly disagree to (7) strongly agree, with a higher score indicating a greater desire to lose weight ($M = 4.98$, $SD = 1.72$, $\alpha = 0.85$).

2.2.4. *Self-objectification*

To measure self-objectification, we utilized the Self-Objectification Questionnaire from Noll and Fredrickson (1998). Although initially identified as a trait measure, it has been used effectively in numerous experimental and panel studies (e.g., Aubrey, 2006; Aubrey et al., 2009; Pennell & Behm-Morawitz, 2015) to demonstrate state-level change in self-objectification, due to priming of a stimulus (e.g., slimming filter image exposure). This measure asks participants, "How important are these attributes to your self-concept? From most important (1) to least important (10), please rank the following attributes." These attributes include five appearance/desire-based attributes, like weight and sex appeal, as well as five competence-based attributes, like physical coordination and energy level. To calculate the total score on participants' objectification tendencies, we subtracted the sum of the appearance/desire measures from the competence measures. Therefore, within the composite measure, a lower score indicated greater self-objectification ($M = 1.89$, $SD = 2.66$).

2.2.5. *Anti-fat attitudes*

To assess anti-fat/fatphobic attitudes, which is the extent to which people hold negative attitudes toward overweight individuals and personal weight gain, we utilized Crandall's (1994)Anti-fat Attitudes Scale. This included a total of 13 items across three subscales (dislike, fear of fat, and willpower), such as "I really don't like fat people much" and "Fat people make me feel somewhat uncomfortable." Responses ranged from (1) strongly disagree to (7) strongly agree), with a higher score indicating greater fatphobic attitudes ($M = 2.97$, $SD = 1$, $\alpha = 0.85$).

2.2.6. *Social media use*

As a control variable, we were interested in measuring participants' social media usage, as those higher in social media use may be more susceptible to the effects of social comparison, including with filter usage as they experience greater exposure. Therefore, to capture this, we asked participants, "Approximately, how many hours per day do you spend interacting with social media (e.g., TikTok, Instagram, Twitter, Facebook, etc.)?" They were then able to select zero hours to over 10 h from a drop-down menu ($M = 2.6$, $SD = 2.32$).

2.2.7. *State comparison*

State comparison measured both social self-comparison and social comparison, depending on the condition. Social self-comparison was captured using an adapted version of Tiggemann and McGill's (2004) state appearance comparison scale. Three items were constructed to match the stimuli of each condition. For example, the social comparison questions in condition one ($M = 4.85$, $SD = 1.89$, $\alpha = 0.85$) and three ($M = 3.94$, $SD = 1.78$, $\alpha = 0.85$) included: To what extent did you think about your unfiltered appearance when seeing your filtered appearance? To what extent did you compare your overall unfiltered appearance with your filtered appearance? To what extent did you compare unfiltered

specific body parts (like your face) with your filtered appearance? Questions in the second condition ($M = 2.68$, $SD = 1.96$, $\alpha = 0.85$) included traditional social comparison items: To what extent did you think about your own appearance when watching the person using a filter? To what extent did you compare your overall appearance with the person using a filter? To what extent did you compare specific body parts (like your face) with that of the person using a filter?

3. Results

3.1. Social comparison and social self-comparison

First, H1 was tested using analysis of variance to decompose the direct effects of condition on state comparison (i.e., social comparison and social self-comparison) in order to examine significant group differences. Social media use was entered as a covariate in the model. Results revealed that the condition (see Table 1) significantly predicted the level of state comparison, $F(1, 185) = 23.20, \eta_p^2 = 0.20, p < .001$ (see Table 2). To further understand the extent of difference between conditions, Tukey HSD post hoc tests revealed significant differences between conditions 1 and 2 (*mean difference* $= 2.16, p < .001$), conditions 1 and 3 (*mean difference* $= 0.91$, $p < .05$), and conditions 2 and 3 (*mean difference* $= -1.26$, $p < .001$). In other words, state comparison was greatest for those in condition 1, followed by condition 3 and then condition 2. State comparison in condition 1 (i.e., using the slim beauty filter) was measured using *social self-comparison*, the new construct proposed in this research. Our finding suggests viewing a filtered image of the self resulted in greater comparison processes than viewing a filtered image of another person.

Next, hypothesis 2 examined state-level comparison as a mediator of the relationship between condition and the outcome variables. The indirect effects models were tested using Hayes' PROCESS version 4.2 model 4. In the models, Condition 1 was used as the referent condition, and two contrasts were tested: Condition 2 vs. Condition 1 (X1) and Condition 3 vs. Condition 1 (X2). Significant indirect effects models are indicated by Lower Limit Confidence Intervals (LLCI) and Upper Limit Confidence Intervals (ULCI) that do not contain zero. Social media use was entered as a covariate. State comparison mediated the relationships between condition and the following outcomes: self-objectification, $F(4, 182) = 4.03, R^2 = 0.08, p < .001$; desire to lose weight, $F(4, 182) = 2.97$, $R^2 = 0.06, p < .05$; and anti-fat attitudes, $F(4, 182) = 5.68, R^2 = 0.11, p < .05$. Please refer to Table 3 for full indirect effects model results examining condition differences.

Conditions 2 (i.e., viewing slimming filter on other person) and Condition 3 (i.e., using color filter on self) both significantly differed from Condition 1 (i.e., using slimming filter on self), such that Condition 1 produced greater comparison levels than the other conditions, which in turn significantly predicted more negative outcomes. In short, social self-comparison—the novel form of social comparison developed in our research—fostered more negative attitudes toward fatness, higher levels of self-objectification, and desire to be thinner.

Table 2
Levels of body dysmorphic cognitions and state comparison predicted by condition.

Variable	Condition 1 Mean (SD)	Condition 2 Mean (SD)	Condition 3 Mean (SD)
Body dysmorphic cognition	3.63 (1.37)[a]	3.38 (1.26)	3.09 (1.08)[a]
State comparison	4.85 (1.89)[bc]	2.68 (1.96)[bd]	3.94 (1.78)[cd]

[a]Conditions 1 and 3 were significantly different for body dysmorphic cognitions.
[bc]Condition 1 was significantly different from both Conditions 2 and 3 for state comparison.
[bd]Condition 2 was significantly different from both Conditions 1 and 3 for state comparison.
[cd]Condition 3 was significantly different from both Conditions 1 and 2 for state comparison.

Table 3
Indirect effects of condition on dependent variables through state comparison.

Dependent Variable	Contrast	b	SE	LLCI	ULCI
Body ideal discrepancy	X1	0.148	0.12	−0.083	0.392
	X2	0.065	0.06	−0.037	0.198
Self-objectification	X1*	0.572	0.26	0.123	1.122
	X2*	0.252	0.15	0.025	0.590
Preference for filtered image	X1	−0.051	0.11	−0.278	0.179
	X2	−0.022	0.05	−0.141	0.082
Desire to lose weight	X1*	−0.406	0.16	−0.756	−0.110
	X2*	−0.179	0.10	−0.414	−0.024
Anti-fat attitudes	X1*	−0.273	0.10	−0.482	−0.101
	X2*	−0.12	0.06	−0.265	−0.021

Note. The indirect effects model results for X1 indicate the difference between Condition 1 and Condition, and the results for X2 indicate the difference between Condition 1 and Condition 3. Condition 1 (i.e., using the slimming beauty filter) was indicated as the reference group.
* Denotes significant total indirect effects for the outcome variable.

However, state comparison did not mediate the relationships between filter usage and body ideal discrepancy, nor preference for the filtered image; meaning engaging in state comparison to the filtered image did not create a larger gap between one's current body size and ideal body size, nor did it make people wish they looked like their filtered image. However, there was a direct effect of condition on preference for the filtered image, $t = 4.88, p < .001$ (LLCI = 0.3686, ULCI = 0.8683). Analysis of variance was utilized to examine differences by condition. Condition significantly predicted preference for the filtered image, $F(2, 186) = 19.62, p < .001, R^2 = 0.17$. Tukey HSD post hoc tests revealed significant differences between conditions 1 and 2 (*mean difference* $= -1.20, p < .001$), conditions 1 and 3 (*mean difference* $= -1.22$, $p < .001$). There were no significant differences between conditions 2 and 3 (*mean difference* $= -0.02, p = .99$). Taken together, these results suggest that participants who used the slimming filter preferred that image to their real self to a greater degree than those who used the neutral color-changing filter and those who watched someone else use the slimming filter.

3.2. Body dysmorphic cognitions

Hypothesis 3 examined the direct effect of condition on body dysmorphic cognitions. Results revealed that condition significantly predicted level of body dysmorphic cognitions ($F(2, 184) = 14.26$, $R^2 = 0.13, p < .001$), $t = -2.63$, $p < .01$ (LLCI = −0.5315, ULCI = −0.0758). Mean scores revealed that participants who used the slim beauty filter had the highest level of body dysmorphic cognitions, followed by participants who watched a video of another person using a slim beauty filter, and finally, those who used a color filter (see Table 2). However, not all group differences were significant. Results revealed that conditions 1 and 2 as well as conditions 2 and 3 were not significantly different from one another. However, conditions 1 and 3 were significantly different from one another, such that body dysmorphic cognition was higher after participants used a slim beauty filter in comparison to using a color filter, $t(106) = 2.21$, $p < .05$).

The indirect effects models for hypothesis 4 were tested using Hayes' PROCESS version 4.2 model 4. In the models, Condition 1 was again used as the referent condition, and two contrasts were tested: Condition 2 vs. Condition 1 (X1) and Condition 3 vs. Condition 1 (X2). Significant indirect effects models are indicated by LLCI and ULCI that do not contain zero. Social media use was again entered as a covariate in the model. The relationships between condition and all outcome variables were significantly mediated by body dysmorphic cognitions, but only when looking at differences between Conditions 1 and 3 (X2). Please see Table 4 for full results. Using the slimming filter fostered higher body dysmorphic cognitions, in comparison to using the color filter, which in turn resulted in stronger body ideal discrepancy, desire for weight loss, self-objectification, preference for the filtered image, and anti-fat

Table 4
Indirect effects of condition on dependent variables through body dysmorphic cognition.

Dependent Variable	Contrast	b	SE	LLCI	ULCI
Body ideal discrepancy	X1	0.071	0.07	−0.061	0.223
	X2*	0.192	0.09	0.047	0.388
Self-objectification	X1	0.196	0.19	−0.145	0.594
	X2*	0.526	0.22	0.144	0.983
Preference for filtered image	X1	−0.047	0.05	−0.162	0.032
	X2*	−0.126	0.07	−0.281	−0.015
Desire to lose weight	X1	−0.128	0.12	−0.381	0.109
	X2*	−0.344	0.14	−0.634	−0.100

Note. The indirect effects model results for X1 indicate the difference between Condition 1 and Condition, and the results for X2 indicate the difference between Condition 1 and Condition 3. Condition 1 (i.e., using the slimming beauty filter) was entered as the reference group.
* Denotes significant total indirect effect for the outcome variable.

attitudes.

There were no significant differences between Conditions 1 and 2 when examining the indirect effects of condition on our outcome variables through body dysmorphic cognitions. Taken together, the results of Hypothesis 4 indicate that that using a slimming filter on an image of oneself was associated with more negative outcomes in comparison to using a neutral filter.

4. Discussion

Social self-comparison is a novel concept to formalize the everyday experience afforded by digital advancements in AR technology – making comparisons to your mediated, filtered self possible. With the prominence of social media in our daily interactions, filter usage has a social element in two ways. First, filters allow users to engage in conforming to societal expectations around beauty. People can use beauty filters that make them appear thinner, have smoother skin and longer lashes, and other standards for the idealized appearance (Eshiet, 2020). Second, it is a social experience due to the nature of social media, resulting in a shared experience of using filters that other people are using and posting filtered images and videos for other users to see. In this way, users are also thinking about the imagined audience – in turn, a cycle is created of posting filtered images and expecting filtered images of others (Lavrence & Cambre, 2020). These expectations may feed into the thin idealized beauty standards in the US among these social media users.

It is no secret then that filters create expectations around beauty and how to present oneself online (Eshiet, 2020). As our study shows, they also have the ability to deepen the stigma around fatness. While much work has been done on social comparison on social media (e.g., Verduyn et al., 2020), little is conceptualized about the related phenomenon of comparing oneself to a digitally altered version of the self. Therefore, our current study pushes forward thinking about how to expand theorizing of social comparison to include social self-comparison to examine how digitally altered images of the self impact self perceptions.

As our results highlight, using a filter was more potent in participants' subsequent state comparisons. In other words, participants using a filter were more likely to make comparisons (in this case, to their filtered image) than those watching someone else use a filter. This provides evidence of our proposed extension to social comparison theory. It is clear that beauty filters have created deeper opportunities for state comparisons, highlighting the importance of considering social self-comparison in body image research. This is especially important as we consider the outcomes of comparison in the digital environment.

The current study found that, when experiencing state-level comparison as a result of filter use, users felt worse about their real-life image. Specifically, the process of social self-comparison—or comparing one's real self to an augmented version of the self via a social media filter—fostered more negative effects. This manifested specifically in their desire to lose weight after seeing themselves in a slimmer way. They also were more likely to view their body as an object, evaluating themselves and their worth based on their appearance. Additionally, they experienced a greater disdain for fatness. Therefore, filter usage resulting in state comparison (via social self-comparison) has negative implications for how users subsequently feel about themselves and their bodies. Although these effects are not large, they are statistically significant and account for some variance in explaining why individuals may feel poorly about themselves after using social media filters.

The dependent variables measured in this study also are linked with other negative health outcomes, thus suggesting that future research may further explore other impacts of using social media beauty filters. For example, engaging in self-objectification may result in increased sexual dysfunction and disordered eating, among other negative outcomes (Rolnik et al., 2010; see Daniels et al., 2020 for a review; see Moradi & Huang, 2008 for a review). Additionally, with filter users experiencing a greater disdain toward fatness as a result of comparisons, this may lead to the deepening of weight stigma and dislike toward overweight individuals. Therefore, filter usage may have additional alarming consequences. Future research may examine such outcomes.

Beyond state comparison, body dysmorphic cognition was an important mediator in the relationship between filter consumption and body image-related outcomes. Although traditionally thought of in a clinical sense via body dysmorphic disorder (e.g., Phillips, 1998), body dysmorphia may operate similarly to self-objectification in that it is indeed a trait, but can be made salient in certain situations. Additionally, we intentionally only measured this using the cognitions subscale of the Body Dysmorphia Scale (BDD-SS). This omitted behavioral outcomes of body dysmorphia, as we were instead interested in participants' internal thoughts that they may be ruminating on as a result of the filter usage. These cognitions may be more widely experienced outside of a clinical sense given their closeness to other measures such as body dissatisfaction.

Our results found that body dysmorphic feelings were indeed primed by filter usage, such that filter usage led to participants experiencing a saliency effect, or heightened body dysmorphia. By experiencing body dysmorphic feelings as a result of the filter, participants were further impacted to experience great body ideal discrepancy, meaning they had a larger gap between their current body size and ideal body size. Unsurprisingly then, they also preferred their filtered image over their real-life appearance and had a greater desire to lose weight. They also were more likely to objectify themselves. Additionally, they experienced greater anti-fat or fatphobic attitudes.

Regarding differences in the mediation effects for each condition, using filters on the self resulted in higher levels of comparison, as compared to watching someone else use a filter. This is as expected, given that the mediated self is a closer object for comparison. Additionally, those using the beauty filter had higher levels of body dysmorphic cognitions compared to those using the color filter, although there were no significant differences from the body dysmorphic thoughts experienced by those watching someone else use a filter. This is unsurprising given that watching someone alter their appearance in a desired way, or altering your own appearance, is more likely to result in experiencing body-related concerns (Eshiet, 2020; Javornik et al., 2022; Beos et al., 2021; Sun, 2021). Both using and watching others use the slimming beauty filter results in more pronounced anti-fat attitudes, suggesting that filters not only promote comparison processes but also heighten negative beliefs about overweight or fat individuals. Our research findings suggest that slimming filters may have a negative effect on people's body-related perceptions as well as cultivate a narrow view of beauty that does not include larger-sized individuals.

4.1. Theoretical implications

The current study advances social comparison theorizing to include a

novel concept: social self-comparison. As the study results confirm, social self-comparison is a powerful mechanism that may be triggered by beauty filters, leading to a slew of negative outcomes for users. In this way, social media and the advancement of AR have begun to allow users easily accessible and often realistic ways to view themselves, including in desirable ways. Through using beauty filters, users are able to make comparisons between their real-life appearance and their mediated image. As results indicated, social comparison was greatest amongst those in the social self-comparison condition, followed by the condition in which someone else was using a filter. Therefore, the current study continues to find support for social comparison and its effects, but further expands our understanding of comparison processes to showcase the strength of social self-comparison.

Previous social comparison literature has focused on making comparisons to others, leading to either positive or negative self-evaluations (e.g., Buunk & Gibbons, 2007). In the current study design, not only are people engaging in self-comparisons through filters, but often walking away likely to have experienced negative self-evaluations. For example, the participants tasked with using a slimming beauty filter were able to see thinner, filtered images of themselves, leading them to want to lose weight and even feel a greater dislike toward fatness. They also engaged in more self-objectification, highlighting the pervasiveness of filter usage in appearance anxiety and self-concept (e.g. Calogero, 2012).

Recent research shows that beauty filters decrease body satisfaction, and the current study expands the ways in which that dissatisfaction may manifest (Dijkslag et al., 2024). As Dijkslag and colleagues (2024) note, this finding may be due to social comparison processes, although they did not directly evaluate this. However, the current study is able to formally solidify social comparison processing in the effects of beauty filters, as well as expand the field of social comparison theorizing. Although the study by Dijkslag and colleagues (2024) did not see support for the role of self-identification in the usage of beauty filters and their associated outcomes, the current study supports the idea that social self-comparison may be more powerful than traditional social comparison, showcasing the need for further exploration in this vein.

4.2. Practical implications

Filters are present in our everyday lives, and using them has become ingrained into the experience of digital life in society. Although some filters may seem silly or harmless, others may lead to detrimental consequences. Some of the practical implications of this study include the expectations set by slimming filters for users, as they picture themselves how they could look having lost weight. From this filter usage, users are led to compare themselves to their filtered image as well as experience heightened body dysmorphic feelings. In turn, filters lead users to feel poorly about themselves and wish to change their appearance through weight loss for appearance reasons, rather than health reasons. There may be additional practical (and theoretical) implications regarding stigma, as slimming filter usage causes a deeper dislike of fatness. In turn, slimming and other beauty filters also elicit ethical considerations, as users may feel poorly about themselves and others as a result of their usage. Social media developers may learn from this research that slimming filters are a detriment to users given their psychological harm. We recommend to practitioners that they practice ethical design and have AI/IT designers and User Experience (UX) researchers consider the empirical research that points to the negative effects of beauty filters. In turn, developers may consider eliminating these types of filters, as well as social media platforms, instead offering users more body-neutral options.

The results also expand our understanding of beauty filters in making salient experiences of body dysmorphic thoughts. As mean scores indicated, body dysmorphic cognition was greatest amongst those in the social self-comparison condition, followed by the condition in which someone else was using a filter. Although only the social self-comparison condition and control were statistically significantly different from one another, results show that whether by using a filter or watching someone else use one, body dysmorphic thoughts may become salient, leading to other negative body-related evaluations. In other words, seeing oneself "beautified" leads to the self-perception of one's appearance being flawed. The same thing occurs in seeing someone else using a filter. This further builds on research highlighting social media as a source for making body dysmorphia salient as well as causing related outcomes (Rizwan et al., 2022; Raj et al., 2022).

4.3. Limitations and future directions

Limitations of this research include the generalization of our findings to the multitude of real-world scenarios that may be encompassed in using beauty filters in the social media landscape. We tested one slimming filter that has a relatively subtle effect, whereas other filters popular on TikTok and Instagram may produce other effects and more profound effects on digital images and videos. It is not unreasonable to assume that beauty filters, collectively, may have some similar effects on social media users. However, differential effects may also emerge for various digital manipulations afforded by social media filters. We also rely on self-report data, which may not fully capture the extent of filter usage. Additionally, we employed an experimental design that lacks ecological validity; in this way, participants did not get to choose what filter they used. In turn, the study's external validity may not harness the impact of real-world implications. For example, not all participants may want to use the study's filters in the real world, lessening the robustness of conclusions drawn by the results.

Additionally, the average age of our participants was 36 which does not represent Generation Z social media users. Rather, the majority of our participants were Millennials who are engaging with filters alongside younger generations but potentially from different life experiences and with different effects. Further, the majority of our sample consisted of women. Future research should look further into how slimming filters, or filters that show heightened muscularity, impact men. Additional research may also seek to replicate this study with additional social media audiences to determine how effects may be similar or different based on generation and culture. Finally, our research provides a foundation for the study of social self-comparison. Future research should further unpack specific instances in which social self-comparison may be stronger.

5. Conclusion

Taken together, the results of our research support the notion that beauty filters may have a negative effect on body image, fostering internalization of unrealistic beauty standards. This is consistent with prior studies (Alsaggaf, 2021; Moreschi & Aaron, 2024) and extends knowledge of the processes at play in determining the effects of filter usage on cognitive outcomes. Specifically, using a slimming beauty filter resulted in greater comparison processes than watching another person use a beauty filter or using a simple color (blue) filter on one's image. Additionally, using a beauty filter resulted in greater comparison processes than using a color filter. The relationships between beauty filter use and body-related perceptions may be complex. Comparison processes mediated the relationship between condition and desire to lose weight, self-objectification, and anti-fat attitudes. However, comparison processes did not predict body ideal discrepancy or preference for the filtered image. In other words, a person's level of social/self-comparison after condition exposure did not predict the gap between their current and preferred body size, or their predilection for the filtered image. This may be because comparison is not the correct mechanism to examine the relationship, but instead, these outcomes may be more directly related to how a person feels about their appearance, such as body dysmorphia.

Our study highlights the dangerous relationship between filter use and body dysmorphia, as this relationship serves as a mechanism for negative body-related outcomes and a pressure to be more like one's

filtered image. Body dysmorphia mediated the relationships between condition and all outcome variables, suggesting that using slimming beauty filters may negatively impact people's body-related perceptions in terms of body dysmorphia and then, in turn, result in greater body dissatisfaction and negative body-related beliefs.

CRediT authorship contribution statement

Makenzie Schroeder: Writing – original draft, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Elizabeth Behm-Morawitz:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Formal analysis, Data curation.

Declaration of competing interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chb.2024.108519.

Data availability

The authors do not have permission to share data.

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Snapchat lenses and body image concerns

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Abstract

Snapchat allows users to apply lenses to photographic content, with these lenses often enhancing physical appearance. This may lead users to adopt unrealistic ideals of physical appearance. In a two-part study with college students, this investigation explored associations between general use of Snapchat lenses and body image concerns, and experimentally examined how taking selfies with Snapchat lenses influences appearance satisfaction. Taking more photos using Snapchat lenses, in general, was associated with greater body image concerns. However, there was little experimental evidence indicating that taking selfies with lenses influences state appearance satisfaction relative to an appearance-neutral control. There was no evidence of gender moderation. Notably, taking more selfies without lenses until reaching one satisfactory for posting on social media was associated with greater body image concerns.

Keywords

Body image, Snapchat, social media, social networking sites

Snapchat is a highly visual social networking site (SNS) involving the exchange of photographic and video content. Aided by enhancement tools such as filters and lenses, the use of highly visual SNSs may exacerbate body image concerns. Specifically, exposure to others' appearance-oriented content can negatively influence one's own body image

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(Fardouly and Vartanian, 2016; Holland and Tiggemann, 2016). Less research has examined body image associations for producers of content. Moreover, most existing research has focused on SNSs such as Facebook and Instagram. Little attention has been devoted to Snapchat, despite its popularity among US young adults (Perrin and Anderson, 2019). This study examined how using Snapchat lenses, a tool that can be used enhance one's appearance, relates to body image concerns.

Social networking sites and body image

SNS users often engage in highly positive self-presentation (Reinecke and Trepte, 2014). Users can be selective with how their appearance is represented in online images, through choosing which images to upload, editing images, or removing unattractive images (Fardouly and Vartanian, 2016). Snapchat lenses are one tool that can edit and enhance images. Research consistently shows that engagement in appearance-oriented activities (e.g. photo activities), rather than general SNS use, is uniquely associated with body image concerns (Choukas-Bradley et al., 2019, 2020; Cohen et al., 2017, 2018; Meier and Gray, 2014). The importance of appearance-oriented content is also emphasized in experimental research, with evidence suggesting that browsing attractive photographic Instagram content increases body image concerns (e.g. Brown and Tiggemann, 2016; Cohen et al., 2019; Tiggemann et al., 2018; Tiggemann and Zinoviev, 2019).

Previous experimental studies have focused on the effects of exposure to other-produced content, rather than self-produced content. Based on objectification theory, there is reason to believe that self-produced, appearance-oriented content may also relate to body image concerns. The theory suggests that girls and women (and, in contemporary applications, boys and men; Moradi and Huang, 2008, but also, see Davids et al., 2019) are embedded in sociocultural environments that emphasize physical appearance (Fredrickson and Roberts, 1997). Individuals are not viewed in relation to their personhood, but as bodies that exist for others' consumption. Objectification theory posits two processes: self-objectification and body surveillance. Self-objectification is the act of viewing one's own body through the perspective of an observer, and is behaviorally manifested as body surveillance, or a preoccupation with and monitoring of one's body (McKinley and Hyde, 1996). Objectification theory acknowledges how the media depicts an often-unattainable beauty ideal (Fredrickson and Roberts, 1997), and SNSs serve as a new outlet through which objectification can occur (Choukas-Bradley et al., 2019, 2020).

Self-produced, appearance-oriented content such as selfies could be linked to objectification processes and body image concerns, with potential differences between posting and editing selfies. Posting selfies is generally associated with higher body satisfaction (Cohen et al., 2018; Ridgway and Clayton, 2016). In contrast, photo editing and photo investment (i.e. the effort and concern individuals give to photos they post on SNSs) are associated with greater body image concerns, especially photo investment (Cohen et al., 2018; Fox and Rooney, 2015; Lamp et al., 2019; McLean et al., 2015; Modica, 2020; Veldhuis et al., 2020). The current research examined taking photographs using Snapchat lenses, with a special focus on selfies. Selfies are commonly taken with a front-facing smartphone camera, allowing the photo-taker to view themselves on their smartphone screen. This cultivates a high salience of the individual's physical appearance. By directly

viewing their projected image, one can adjust their facial expression, positioning, and external environmental cues (e.g. lighting) to optimize the photo. Thus, the selfie experience is inherently objectifying, as photo-takers can self-objectify by viewing their appearance from the perspective of an observer (Salomon and Brown, 2020). Snapchat lenses can further incite objectification. Although lenses are constantly changing, most serve to enhance one's appearance (Lavrence and Cambre, 2020). Users can experiment with different lenses when taking selfies until capturing the desired photograph, potentially further increasing self-objectification. Moreover, experimentation with different lenses could represent body surveillance, as users can inspect their appearance as they flip through different lenses.

Although the experience of taking lensed selfies over Snapchat is likely to be self-objectifying, the effects of taking these photos still require testing. Appearance-enhancing lenses tend to conform to sociocultural expectations of beauty that are often impossible to attain (e.g. smooth skin, large eyes). Therefore, using lenses may remind the photo-taker that they fall short of these standards, which could impair appearance satisfaction. Alternatively, people with pre-existing body image concerns may be drawn to using more appearance-enhancing lenses, as they may feel uncomfortable with their physical appearance and use lenses to take a more satisfactory photo. To date, little research has experimentally examined the effects of taking selfies. One study with female college students found that taking and posting a selfie on Facebook or Instagram decreases self-perceived attractiveness, regardless of if the selfie was edited (Mills et al., 2018). However, this study did not distinguish between taking and posting selfies, a needed distinction as these may have different associations (Yellowlees et al., 2019). A second study with college students addresses this limitation, finding that taking a selfie increased self-objectification regardless of if the selfie was subsequently posted on Facebook (Salomon and Brown, 2020). However, this study did not examine the role that selfie editing may play, which may have additional pernicious effects. Finally, a study with female college students found that inducing body dissatisfaction did not change the time spent or extent of editing made to selfies, but selfie editing increased facial dissatisfaction (Tiggemann et al., 2020).

Examining Snapchat as a medium

Editing tools are present on most SNS platforms (e.g. Instagram filters). We elected to focus on Snapchat for several interrelated reasons. First, self-produced content may be more common on Snapchat compared with other platforms, such as Facebook and Instagram (Burnell et al., 2020). Snapchat is a more visual alternative to text messaging, with users engaging in back-and-forth communication with close others (Duffy and Chan, 2019; Piwek and Joinson, 2016; Vaterlaus et al., 2016). Second, an examination of self-produced content on Snapchat may be beneficial for ecological validity. If self-produced content is common on Snapchat, an experimental test of this content may be more applicable in understanding effects of daily life experiences. In contrast, an experimental examination manipulating Facebook or Instagram content in the same nature as the current research may be less generalizable if self-produced content is much rarer on these platforms. Third, selfies are frequently transmitted via Snapchat (Bayer et al., 2016;

Piwek and Joinson, 2016), suggesting that users may often exchange appearance-oriented content. This highlights a need to understand how Snapchat use may be linked with body image concerns. However, research testing this link is scarce, with only one known study assessing and finding that Snapchat users had elevated disordered eating scores compared with non-users (Wilksch et al., 2019). Although other SNS platforms such as Instagram are also appearance-oriented, a greater frequency of self-produced content on Snapchat would suggest that self-produced, appearance-oriented experiences may occur more often on Snapchat.

It is important to note that Snapchat is unique in its ephemerality, as content is usually automatically deleted shortly after being opened. Despite this ephemerality, Snapchat could still affect state body image. As previously noted, the selfie-taking experience on Snapchat is inherently self-objectifying, exacerbated by appearance-enhancing lenses. Popular press articles detail anecdotes from plastic surgeons of patients requesting procedures that replicate their Snapchat-altered appearance, a phenomenon termed "Snapchat dysmorphia" (e.g. Hunt, 2019). Startlingly, the sentiment of wanting to alter one's appearance to match Snapchat lenses has been echoed in children (Pescott, 2020). Although extreme, these cases demonstrate that Snapchat lenses may have potential body image effects despite the platform's inherent ephemerality. The anecdotal nature of these reports stresses the need for empirical verification. Furthermore, though the available Snapchat lenses are constantly changing, most lenses are united by their appearance-enhancing nature—even lenses that are intended to be humorous[1] (e.g. adding bear or dog ears to one's head).

With the role of objectification in mind, we examined how interacting with Snapchat lenses relates to self-objectification and body surveillance. In addition, we examined relations with facial satisfaction and internalization of the beauty ideal. Because selfies are prominent on Snapchat, facial satisfaction may be particularly important in understanding relations with Snapchat use, as selfies are typically taken portrait-style and emphasize the face (Tiggemann and Zinoviev, 2019). Moreover, objectification theory proposes that the permeation of the beauty ideal plays a key role in the objectification process, and lenses often reflect beauty ideals. Thus, we examined Snapchat lens use in relation to internalization of the beauty ideal, characterized by the extent to which an individual endorses media-imposed sociocultural standards of beauty (Thompson et al., 2004).

The present study

In Study A, we examined how frequency of using Snapchat lenses relates to body image concerns (i.e. facial satisfaction, body surveillance, self-objectification, and internalization of the beauty ideal). We expected that participants who more frequently use Snapchat lenses would report lower facial satisfaction, and greater body surveillance, self-objectification, and internalization of the beauty ideal. Moreover, we hypothesized that these relations would be uniquely associated with Snapchat *lens* use, above and beyond *general* Snapchat use. We examined how the use of Snapchat lenses, in general, relates to body image concerns. However, due to our special focus on selfies (explored in Study B), we also considered links with items solely pertaining to selfies. We also investigated

how gender may moderate these associations. Recent applications of objectification theory suggest that the basic premises can be applied to men as well as women (Moradi and Huang, 2008; Sevic et al., 2020). There is also evidence that the media may influence men and women's body image in similar ways (Huang et al., 2020), including SNSs (Holland and Tiggemann, 2016). However, as Snapchat lenses more closely imitate sociocultural expectations of beauty for women (e.g. smooth skin, large eyes), we predicted that these associations would be present for women and not men.

In Study B, we experimentally examined how taking selfies using lenses on Snapchat changes appearance satisfaction. Participants were randomly assigned to either take 15 selfies using lenses (i.e. lenses condition), take 14 selfies using lenses and then one selfie without lenses (i.e. unaltered condition), or an appearance-neutral control (taking pictures of objects around the room). We expected that, relative to the control, taking 15 selfies with lenses would increase appearance satisfaction, as participants would have been exposed to enhancing pictures of themselves, with no exposure to an unaltered picture of the self. We expected that participants assigned to the unaltered condition would decrease in appearance satisfaction, as they would be reminded of their unaltered appearance and how it may compare with their edited appearance. In addition, we hypothesized that changes across conditions would be observed for women and not men. We further examined whether participants' body image concerns (facial satisfaction, body surveillance, self-objectification, and internalization of the beauty ideal) moderated these changes. We expected that relations would be stronger for those with greater body image concerns. Moreover, we assessed the degree to which participants thought about their appearance (appearance preoccupation) while taking the photos and expected that relations would be stronger for those who reported greater appearance preoccupation.

Some individuals may take multiple selfies before finding one they are comfortable with sharing on SNSs (Lamp et al., 2019). Study B also explored how Snapchat lens use may influence this behavior. After the manipulation, participants were instructed to take selfies without applying lenses until they reached one that they would be happy to post on SNSs. We expected that participants in the two experimental conditions, compared with the control, would take more photos until they reached one with which they were satisfied. As previous research suggests that taking more selfies before posting is correlated with greater body surveillance (Lamp et al., 2019), we also explored the link between number of selfies taken and body image concerns.

Method: Study A

Participants

Participants included 792 undergraduates with a Snapchat account (M_{age} = 20.69, SD_{age} = 3.54; $range_{age}$ = 18–50; 77% female; 44% Asian/Asian-American, 26% White, 17% Hispanic/Latinx, 8% Multiracial/Other, 5% Black/African American). A subsample (n = 518) also completed the experimental procedure (Study B), which was the initial focus of the study. A study advertisement was posted in an online portal where interested students could sign up for an hour-long laboratory session. Data collection took place over the Spring 2019 semester. After the semester, we made the survey items available

via the online portal for students to complete over the Summer 2019 semester. All participants received partial course credit for completing the study. We did not continue the experimental procedure during the summer because (a) an a priori power analysis in G*Power suggested that to detect a small-to-medium effect (f=.15) for our experimental analyses with 80% power and a p value of .05, we needed 357 participants, which we exceeded by the end of the semester and (b) there were limited summer research resources (e.g. personnel). This decision was made a priori and without inspecting the data.

Measures

Snapchat frequency. Participants were asked: "On average, how often do you use Snapchat?," with response options ranging from 1 ("Never") to 11 ("11 or more times per day").

Snapchat lenses use. In the absence of an established measure assessing frequency of using Snapchat lenses, we consulted a group of nine, non-participant undergraduate Snapchat users for item generation. Six items were generated, using an 11-point scale (1="Never," 11="11 or more times per day"). Items were preceded by the stem: "How often do you engage in the following behaviors on Snapchat?". The items were: "Send a photo directly to one or more people, with a filter[2] to make it look better," "Send a photo directly to one or more people, with a filter to make it look silly," "Upload a photo to my story, with a filter to make it look better," "Upload a photo to my story, with a filter to make it look silly," "Send a selfie with a filter directly to one or more people," and "Upload a selfie with a filter to my story." We distinguished between "better" and "silly" filters as we speculated that they would relate to body image concerns differently. However, an exploratory factor analysis using maximum likelihood estimation and direct oblimin rotation suggested that all items loaded on one factor, and internal consistency was acceptable (α=.88).

Facial satisfaction. Participants completed the 10-item facial satisfaction subscale of the Body Parts Satisfaction scale on a 6-point scale (1=Extremely Dissatisfied, 6=Extremely Satisfied; Berscheid et al., 1972; Frederick et al., 2014). Participants were asked "How satisfied are you with the way your body looks" and were provided a series of attributes, such as "Hair" and "Eyes" (α=.86).

Self-objectification. Participants completed the 12-item Self-Objectification Questionnaire (Noll and Fredrickson, 1998). This scale requires participants to rank how important a series of attributes are to their overall physical self-concept. Items are either appearance-based (e.g. "physical attractiveness," "weight") or competence-based (e.g. "health," "physical fitness"). The appearance-based and competence-based items are summed individually, and a difference score is computed that ranges from –36 to 36, with higher scores indicating greater importance on appearance-based attributes (i.e. greater self-objectification).

Body surveillance. Participants completed the 8-item body surveillance subscale of the Objectified Body Consciousness scale on a 6-point scale (1=Strongly Disagree,

Table 1. Zero-order correlations for Study A variables.

	1	2	3	4	5	6	7	8
1. SC freq.								
2. SC lenses	.48**							
3. Body surv.	.14**	.18**						
4. Face satis.	−.03	−.05	−.39**					
5. Self-object	.12**	.12**	.52**	−.27**				
6. Internalization	.10**	.20**	.55**	−.38**	.42**			
7. BMI	−.03	.03	.06	.02	.00	.01		
8. Age	−.28**	−.11**	−.09*	.13**	−.08*	−.12**	.16**	
Mean: female	8.29[a]	3.82[a]	4.02[a]	4.35[a]	−2.17[a]	2.60[a]	23.69[a]	20.74[a]
SD: female	2.58	1.92	.97	.80	18.24	1.23	5.13	3.73
Mean: male	8.24[a]	3.02[b]	3.68[b]	4.37[a]	−8.76[b]	2.26[b]	24.39[a]	20.60[a]
SD: male	2.39	1.89	1.05	.82	17.97	1.05	4.98	2.93

Note. Means with differing subscripts (a, b) differed for men and women at $p < .01$.
$^{*}p < .05$; $^{**}p < .01$.

6 = Strongly Agree; McKinley and Hyde, 1996). A sample item includes "During the day, I think about how I look many times" ($\alpha = .88$).

Internalization of the beauty ideal. Participants completed the 9-item internalization-general subscale of the Sociocultural Attitudes Toward Appearance Scale-3 on a 5-point scale (1 = Definitely Disagree, 5 = Definitely Agree; Karazsia and Crowther, 2008; Thompson et al., 2004). A sample item includes "I try to look like the people on TV" ($\alpha = .96$).

Covariates. Participants reported on their height and weight, which was converted into their body mass index (BMI). In addition, age was included as a covariate due to potential age differences in Snapchat use.

Results: Study A

Descriptive statistics and zero-order correlations are in Table 1. Key study variables were normally distributed. Missing data were limited (<3.8%) and treated with listwise deletion. *T* tests found that women, compared with men, reported more lens use and higher body surveillance, self-objectification, and internalization of the beauty ideal (Table 1). No gender differences were found for Snapchat frequency, facial satisfaction, age, and BMI ($ps > .123$).

Regressions examined unique relations between Snapchat frequency and Snapchat lens use[3] with body image concerns. Multicollinearity diagnostics suggested no issues with multicollinearity (tolerance values > .72). Higher frequency of using Snapchat lenses uniquely predicted body surveillance, self-objectification, and internalization of the beauty ideal, whereas general Snapchat frequency was unrelated to all outcomes (Table 2). There were no significant relations for facial satisfaction. Next, regression analyses examined whether Snapchat lens use interacted with gender (effects coded

Table 2. Study A: Regression analyses predicting body image concerns.

	b [95% CI]	SE	Overall analysis
Body surveillance			$F(4, 733) = 6.70$, $p < .001$; $R^2 = .04$
Snapchat frequency	.02 [–.02, .05]	.02	
Snapchat lenses	.07** [.03, .11]	.02	
Facial satisfaction			$F(4, 734) = 3.06$, $p = .016$; $R^2 = .02$
Snapchat frequency	.01 [–.01, .04]	.01	
Snapchat lenses	–.02 [–.06, .01]	.02	
Self-objectification			$F(4, 720) = 3.50$, $p = .008$; $R^2 = .02$
Snapchat frequency	.44 [–.20, 1.07]	.32	
Snapchat lenses	.80* [.00, 1.59]	.40	
Internalization			$F(4, 733) = 8.90$, $p < .001$; $R^2 = .05$
Snapchat frequency	–.02 [–.06, .03]	.02	
Snapchat lenses	.12** [.07, .17]	.03	

$^*p < .05$; $^{**}p < .01$.

–1 = female, 1 = male) in predicting body image concerns.[4] Lens use was grand-mean centered and the interaction term was formed by computing the cross-product between gender and lens use. Interactions were not significant for any outcome ($ps > .141$).

Method: Study B

Participants

Out of the 792 students who completed the survey items, 518 completed the experimental procedure ($M_{age} = 20.62$, $SD_{age} = 2.91$; range$_{age}$ = 18–42; 77% female; 41% Asian/Asian-American, 26% White, 20% Hispanic/Latinx, 7% Multiracial/Other, 5% Black/African American). *T* tests suggested that, compared with those who only completed the surveys, participants who completed the experiment used Snapchat slightly more ($M_{experiment} = 8.45$, $SD_{experiment} = 2.38$; $M_{survey} = 7.96$, $SD_{survey} = 2.78$; $p = .010$), and used Snapchat lenses slightly more ($M_{experiment} = 3.75$, $SD_{experiment} = 1.88$; $M_{survey} = 3.45$, $SD_{survey} = 2.02$; $p = .032$). A chi-square test indicated racial/ethnic differences between the two groups (χ^2 (4, $N = 788$) = 13.60, $p = .009$) with Asian-American students overrepresented and Hispanic/Latinx students underrepresented in the survey group. There were no other differences on key variables ($ps > .058$).

Twenty-two students terminated their completion of the study before finishing, 80 students did not follow study directions (by either skipping the photo task or by taking an incorrect amount of photos), and 17 expressed extreme suspicion about the study's true nature and hypotheses. These students were excluded, leaving a final sample of 399 participants. Participants who were excluded reported higher BMI ($M_{include} = 23.79$, $SD_{include} = 5.12$; $M_{exclude} = 25.07$, $SD_{exclude} = 5.71$; $p = .024$), but there were no other differences between the two groups on key variables ($ps > .116$). After exclusions, group sizes were unequal, as participants in the experimental conditions were more likely to express

suspicion about the study's hypotheses and not follow the photo task directions. The lens condition consisted of 127 students, the unaltered condition 110 students, and the control condition 162 students.

Procedure

To mitigate the influence of demand characteristics, the study advertisement and consent form framed the study as examining how Snapchat relates to memory (Fardouly et al., 2015). A research assistant noted to participants that the survey contained multiple assessments of self-perceptions, with the rationale that the experimenters need to control for self-perceptions due to their influence on memory. Participants first completed surveys that assessed Snapchat use, body image concerns, and baseline appearance satisfaction. They were then provided a list of 20 appearance-neutral words that they were instructed to memorize in 30 seconds. Next, they received a prompt to notify the research assistant that they were ready to move on.

Participants were then randomly assigned to three possible conditions. In the lens condition, participants were instructed to take 15 selfies using Snapchat filters.[5] In the unaltered condition, participants were instructed to take 14 selfies using Snapchat filters, and then one unfiltered selfie at the end, for a total of 15 pictures. In the control condition, participants were instructed to take 15 pictures of objects around the room. Previous experimental research investigating the effects of taking and posting a selfie on SNSs required participants to take a single photograph (with some allowed to retake the photo; Mills et al., 2018). We opted for a larger range of photographs to cultivate a greater appearance-oriented experience, and specified 15 photographs to mirror previous body image research in which participants are exposed to 15 image stimuli (e.g. Brown and Tiggemann, 2016; Tiggemann et al., 2018; Tiggemann and Zinoviev, 2019). Given the constant updates made to Snapchat's available lenses, we did not instruct participants to use certain lenses.[6] Participants were told to inform the research assistant when they finished the task. The research assistant left the room and recorded participants' time to completion. After the task, participants completed remaining survey questions, which included a post-test assessment of appearance satisfaction, a bogus memory recall task, and a question probing for suspicion about the predictions of the study. The participant's notification to the research assistant about their task completion also served as a check to ensure that they did not move on to the survey without taking the pictures. After completing the remaining survey questions, participants were dismissed. Debriefing occurred via email at the end of the semester.

Measures

In addition to the Study A measures, Study B included the following assessments.

Appearance satisfaction. Before and after the photo task, participants completed seven items adapted and modified from the Body Image States Scale (Cash et al., 2002), using a 9-point scale (1 = "Extremely Dissatisfied," 9 = "Extremely Satisfied"). Items were preceded by the stem, "How satisfied do you feel about each of the following attributes,

right now at this very moment?". This was followed by five attributes: "My physical appearance," "My body size and shape," "My weight," "My face," and "My hair." We added items assessing face and hair satisfaction due to the portrait-style of selfies. Participants also completed items assessing how they currently feel about their looks compared with how they normally feel (1 = "A great deal worse about my looks than I usually feel," 9 = "A great deal better about my looks than I usually feel"), and how they currently feel about their looks compared with the average person (1 = "A great deal worse than the average person looks," 9 = "A great deal better than the average person looks"). An exploratory factor analysis using maximum likelihood estimation and direct oblimin rotation suggested that all items loaded onto one factor, and internal consistency was satisfactory ($\alpha_{post} = .90$).

Appearance preoccupation. Participants completed an item asking: "How much did you think about your appearance when engaging in the photo task?," which used a 7-point scale (1 = No thought, 7 = A lot of thought).

Experimental checks. After the photo task, participants were asked how many photos they took during the task as an additional test for correct task completion. Participants were also asked if they updated their Snapchat story, sent a snap, viewed someone else's content during the photo task, or did anything else on their phones or on the computer during the photo task in an open-ended response. Participants who indicated that they updated their story, sent a snap, or did anything else active when using their phone (e.g. sending a text) were marked as engaging in active use ($n = 26$). Participants who indicated that they viewed someone else's content during the photo task or did something passive when using their phone (e.g. reading a text) were marked as engaging in passive use ($n = 29$). Four participants reported both active and passive use. These variables were included as covariates.

Time to complete task. A research assistant timed the participants during the photo task ($M = 3.22$ minutes, $SD = 1.80$) which was included as a covariate.

Final picture. At the end of the study, participants were directed to take unfiltered selfies until they reached one they would be happy uploading on SNSs. Participants reported how many pictures they took until reaching one that was satisfactory.

Results: Study B

Missing data were low (<4.5% on key variables) and treated with listwise deletion. Preliminary analyses indicated no differences between conditions on BMI, the body image moderators, and pre-browsing appearance satisfaction ($ps > .230$). There were also no differences between conditions for age, gender, and race ($ps > .493$). Conditions did not differ on time taken to complete the photo task ($p = .662$). There were significant differences in appearance preoccupation, $F(2, 396) = 38.71$, $p < .001$. Participants in the lens condition ($M = 4.36$, $SD = 1.82$) and the unaltered condition ($M = 4.45$, $SD = 1.68$)

reported greater appearance preoccupation than the control condition (M=2.72, SD=2.03; ps < .001); the two experimental conditions did not differ (p=.733).

A between-subjects analysis of variance (ANOVA) examined whether conditions significantly differed from each other in number of pictures taken at the end of the task before taking one suitable for SNSs. Two extreme outliers were removed (3 SD above the mean). The analysis was not significant (p=.750). Correlations indicated that, regardless of condition, taking more pictures was associated with greater body surveillance (r=.28), self-objectification (r=.21), and internalization of the beauty ideal (r=.18), and lower facial satisfaction (r=–.25, all ps < .001). It was also positively correlated with appearance preoccupation during the photo task, r=.18, p < .001. A t test indicated that women (M=5.33, SD=4.96) took more pictures than men (M=3.81, SD=2.87), t(386)=2.62, p=.009.

Due to the nested nature of the data (two time points nested within participants), analyses examining changes in appearance satisfaction from pre-photo taking to post-photo taking were run using multilevel modeling, with restricted maximum likelihood estimation and a random intercept included to account for nonindependence. We were interested in examining how each experimental condition compared directly with the control condition, and ran all models twice, with one set of analyses comparing the lens condition with the control condition, and the second set comparing the unaltered condition with the control condition. All models were run controlling for active phone use during the photo task (0=no, 1=yes), passive phone use during the photo task (0=no, 1=yes), the amount of time it took to complete the photo-taking task, BMI, and age.

Overall changes in appearance satisfaction

Changes in appearance satisfaction did not differ between the lens condition and the control condition (p=.797), or between the unaltered condition and the control condition (p=.594).

Moderation

Analyses examined whether gender, each body image variable, and appearance preoccupation significantly moderated changes in appearance satisfaction. For each model, the three-way interaction between condition, time (i.e. changes in appearance satisfaction), and the given moderator was inspected to see if moderation significantly differed between the experimental condition of interest and the control condition. Gender was effects coded (-1=female, 1=male) and the continuous moderators were grand-mean centered.

Lens condition. For the lens condition, interactions were not significant for gender (p=.500), body surveillance (p=.426), facial satisfaction (p=.899), internalization of the beauty ideal (p=.955), or appearance preoccupation (p=.883). There was significant moderation for self-objectification, F(1, 265)=4.68, p=.031. A follow-up analysis with condition dummy coded, using the lens condition as the reference group, indicated a significant interaction between time and self-objectification, b=–.01, 95% confidence

interval (CI)=[–.02, –.00], standard error (*SE*)=.004, p=.013. This interaction was examined at lower (–1 *SD* below the mean) and higher (+1 *SD* above the mean) levels of self-objectification. At lower self-objectification, taking photos with lenses increased appearance satisfaction, b=.22, 95% CI=[.04, .40], *SE*=.09, p=.018). There was no change for those higher in self-objectification, b=–.11, 95% CI=[–.30, .07], *SE*=.09, p=.212).

Unaltered condition. For the unaltered condition, interactions were not significant for gender (p=.131), body surveillance (p=.438), facial satisfaction (p=.229), self-objectification (p=.340), internalization of the beauty ideal (p=.134), and appearance preoccupation (p=.978).

Discussion

This study found that students who report more frequent Snapchat lens use generally report greater body image concerns. However, there was little evidence that using Snapchat lenses affected state appearance satisfaction. There was also no evidence that gender moderated the link between Snapchat lens use and body image concerns. Finally, students who took more pictures until reaching one suitable for SNSs reported higher body image concerns compared with students who took fewer pictures.

Reported lens use and body image concerns

Although Snapchat use and Snapchat lens use were generally correlated with body image concerns to a comparable extent, only Snapchat lens use uniquely predicted body image concerns: greater body surveillance, self-objectification, and internalization of the beauty ideal. These findings are in line with previous research indicating that *how* one is using SNSs matters more than *how much* (Cohen et al., 2017, 2018; McLean et al., 2015; Meier and Gray, 2014), and extends prior results found on Facebook and Instagram to Snapchat.

Surprisingly, there were no significant relations with facial satisfaction, even when focusing solely on items targeting selfies. Facial satisfaction may be particularly important when examining selfies, which emphasize one's face (Tiggemann and Zinoviev, 2019). Longitudinally, posting selfies on SNSs has been found to be unrelated to facial dissatisfaction for Chinese adolescents, but selfie editing and facial dissatisfaction have positive bidirectional associations with each other (Wang et al., 2019). Our assessment of Snapchat lens use combines both posting and editing, and therefore separating out these two components may result in differential effects. Thus, future research should better disentangle how editing and posting selfies may differentially relate to facial satisfaction.

Effects of selfies with lenses on appearance satisfaction

There was little experimental evidence that taking selfies with lenses influences appearance satisfaction. Neither taking 15 selfies with lenses, nor taking 14 selfies with lenses and then one without, differentially influenced appearance satisfaction compared with a

control. It is possible that taking selfies with lenses, on its own, may not be enough to elicit changes in appearance satisfaction. Although photo editing has demonstrated relations with body image concerns, these relations may be more influenced by photo investment (Cohen et al., 2018; McLean et al., 2015).

In addition, there was little evidence of moderation by gender, pre-existing body image concerns, and appearance preoccupation during the photo taking task. There was one exception: for students lower in self-objectification, taking 15 selfies with lenses increased appearance satisfaction, whereas no relation was observed for those higher in self-objectification. Therefore, taking selfies with lenses may be beneficial for those least likely to self-objectify. While taking these presumably appearance-enhancing photos, students higher in self-objectification tendencies may be mindful of their unaltered physical appearance, and therefore may not reap the same immediate benefits. It is important to consider how the benefits for those lower in self-objectification may disappear over time. The unaltered condition was designed with this in mind: after taking a series of presumably appearance-enhancing selfies, re-exposure to one's unaltered appearance may result in the loss of benefits provided by taking appearance-enhancing selfies. Indeed, the same benefits for lower self-objectifying students were not observed in the unaltered condition.[7] Future research should utilize longitudinal methods to examine whether these immediate positive effects are sustainable over time.

This lack of experimental evidence suggests that the correlation between lens use and body image concerns could be driven by poorer body image preceding selfie taking behaviors, rather than body image concerns operating as an outcome (e.g. Veldhuis et al., 2020). One recent study suggests that inducing body dissatisfaction does not influence selfie editing (Tiggemann et al., 2020); however, it is possible that findings may be observed when body image concerns are assessed at the trait level instead of state-induced. Additional research using longitudinal methods is needed to provide more definitive conclusions. The observed null results could also be a result of idiosyncrasies or nuances within the sample or the methodology. For example, it could be that posting matters more than simply taking photos. If students are instructed to take selfies without the possibility of these photos being viewed by others, they may give less conscious thought to the photos that they are taking. However, recent evidence suggests no difference between taking and posting selfies (Salomon and Brown, 2020). In addition, 9-point scales to assess changes in appearance satisfaction may be too narrow; the use of visual analog scales (Heinberg and Thompson, 1995) may detect more subtle changes.

Taking photos before posting on SNSs

There was no evidence that the conditions differed in number of photos participants took before reaching one suitable for SNSs. However, women took more photos than men, and taking more photos was moderately correlated with greater body surveillance, self-objectification, and internalization of the beauty ideal, and lower facial satisfaction. This is in line with previous self-report findings indicating that those higher in body surveillance may take more photos before choosing one suitable for SNSs (Lamp et al., 2019). In addition, women's SNS behaviors may be more motivated by self-presentation than men's (Haferkamp et al., 2012). Thus, women may be more selective in the photos they

choose to upload on SNSs, as they may want to be certain that the selected photos conform to their desired self-presentation style.

Implications

The current findings have implications for understanding how other SNS platforms may relate to body image concerns. It was beyond the scope of this study to examine how using Snapchat lenses may differ from using comparable features on other platforms (e.g. Instagram filters). Given that photo alteration tools across platforms share appearance-enhancing affordances, it is plausible that associations with body image concerns may be comparable with the associations observed in the current research. However, platforms such as Instagram also differ from Snapchat in their norms of use. For example, Snapchat is used as a supplement to text messaging, where users connect with close others and communicate humorous content (Piwek and Joinson, 2016; Vaterlaus et al., 2016). In contrast, Instagram is used to post infrequent, highly curated pictures to a larger audience (Underwood and Ehrenreich, 2017).

On the one hand, correlations between using photo enhancement tools and body image concerns may be stronger on Snapchat. The fleeting and rapid nature of Snapchat communication may result in those with greater body image concerns more frequently using Snapchat lenses, and therefore more often interact with a highly appearance-oriented and appearance-enhancing environment. On the other hand, Instagram posts are more effortful. Some users are focused on posting exclusively appearance-enhancing content with the hopes of accruing a large amount of likes and comments (Chua and Chang, 2016). This suggests that Instagram filter use may be more strongly associated with body image concerns, as users may be more engrossed in the appearance-enhancing experience that precedes Instagram posts (Chua and Chang, 2016). Photo investment may be more strongly linked with body image concerns than photo editing (Cohen et al., 2018; McLean et al., 2015), and the phase in which one prepares a photo for Instagram may reflect this process. Moreover, although our experiment did not involve posting or sending pictures, it is plausible that the imagined audience of each platform may influence body image concerns. If Snapchat is used to connect with close others, then users may be less mindful of their physical appearance when taking pictures on this platform. Conversely, taking pictures while being mindful of the larger Instagram audience may be more influential for body image concerns. Future research is needed to examine how SNS platforms may differentially promote associations between using photo enhancement tools and body image concerns.

The present findings also have implications for the role of gender, as gender did not emerge as a significant moderator in any analysis. This was unexpected given that Snapchat lenses generally conform to feminine expectations of beauty. However, recent research suggests that the media influences men and women's body image similarly (Holland and Tiggemann, 2016; Huang et al., 2020). Although certain features of Snapchat lenses more closely conform to feminine expectations of beauty (e.g. enlarging eyes), they nonetheless have appearance-enhancing effects that may be attractive to all users (e.g. removing blemishes). Studies examining men have found that photo editing is linked with body image concerns (Fox and Rooney, 2015; Modica, 2020), with experimental research

finding no moderation by gender when examining effects on self-objectification when taking or posting a selfie (Salomon and Brown, 2020). The lack of gender differences in the current research suggest that associations with Snapchat lenses may be similar for men and women, highlighting a need for greater inclusion of all genders in future research.

Limitations and conclusions

Findings must be considered in the context of several limitations. First, over 100 participants were eliminated from the experimental procedure, which may have reduced power to detect effects. However, our final sample size was still appropriate to detect small-to-medium effects. Second, assessments of Snapchat lens use and the experimental instructions of taking photos were rather broad. Most self-report items did not distinguish between taking selfies and taking photos of others. Furthermore, the experimental instructions did not direct which lenses participants should use. This is because Snapchat lenses are constantly changing, and the lenses available to participants can differ day-to-day. Supplemental analyses suggested that the type of lens used did not moderate the results. However, these items were broad, subjective, and not explicitly appearance-oriented. Therefore, more research is needed to determine how specific types of lenses may influence results. Third, taking only one photo after taking 14 selfies without lenses may not have been a strong enough manipulation to observe results in the unaltered condition. Future research should examine if the number of unaltered selfies taken influences relations with body image concerns. Fourth, the recruited sample was overwhelmingly female, which may have reduced power to detect more subtle gender differences.

Overall, this study provides support for how using Snapchat lenses is related to greater body image concerns, but that taking selfies with lenses may not influence appearance satisfaction in the moment. Findings provide tentative support for how taking selfies with lenses on Snapchat may not necessarily cause body image concerns, and these results could provide a foundation for sorely needed future studies that establish the temporal ordering of the link between Snapchat lens use and body image concerns.

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Supplemental material

Supplemental material for this article is available online.

Notes

1. For the lenses available at the time of manuscript preparation, over four-fifths were appearance-enhancing, with the remaining lenses distorting one's face (e.g. stretching or shrinking it).
2. We used the term "filter" in our items because the initial group of nine undergraduate students suggested that "filter" was more commonly used than "lenses" for the population from which the sample was pulled. Qualitative research also indicates the colloquial use of "filters" when describing Snapchat lenses (Lavrence and Cambre, 2020).
3. Analyses were also run by limiting Snapchat lens use to the two items assessing selfies. These analyses generally paralleled those reported in Table 2, with one notable exception: selfie lens use was only a marginal predictor of self-objectification ($p = .062$).
4. Analyses examining only the selfie items also found no significant interactions with gender ($ps > .560$).
5. As was the case with the survey items, we used the term "filters" in instructions to participants as this was the colloquial term they were more familiar with.
6. At the end of the study, we asked participants in an open-ended response how many photos they took using (a) filters that made the photo look better but not silly, and (b) filters that made the photo look better and also silly. We examined these variables as potential moderators in assessing changes in appearance satisfaction; these analyses were not significant (see supplemental materials).
7. A direct comparison of the lenses and unaltered conditions for self-objectification moderation found that the two conditions differed from each other ($p = .017$), with no moderation observed in the unaltered condition ($p = .189$).

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RESEARCH

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The mediating role of anxiety and depression between problematic social media use and bulimia nervosa among Lebanese university students

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Abstract

Background Bulimia nervosa (BN) is a disorder that is characterized by binge eating and inappropriate compensatory behavior to control weight. The aim of this study was to evaluate the mediating role of anxiety and depression between problematic social media use (PSMU) and BN among a sample of Lebanese university students.

Methods This cross-sectional study was carried out between July and September 2021; a total of 363 university students was recruited through convenience sampling. The PROCESS SPSS Macro version 3.4, model four was used to test the indirect effect and calculate three pathways. Pathway A determined the regression coefficient for the effect of PSMU on mental health issues (depression/anxiety); Pathway B examined the association between mental health issues on BN, and Pathway C' estimated the direct effect of PSMU on BN. Pathway AB was used to calculate the indirect effect of PSMU on BN via depression/anxiety.

Results Results showed that depression and anxiety partially mediated the association between PSMU and BN. Higher levels of PSMU were associated with more depression and anxiety; higher depression and anxiety were associated with more BN. PSMU was directly and significantly associated with more BN. When entering anxiety (M1) then depression (M2) as consecutive mediators in a first model, the results showed that only depression mediated the association between PSMU and bulimia. When taking depression (M1) then anxiety (M2) as consecutive mediators in a second model, the results showed that the mediation PSMU → Depression → Anxiety → Bulimia was significant. Higher PSMU was significantly associated with more depression, which was significantly associated with more anxiety, which was significantly associated with more bulimia. Finally, higher PSMU was directly and significantly associated with more bulimia

Conclusion The current paper highlights the relationship that social media use has on BN and other aspects of mental health such as anxiety and depression in Lebanon. Future studies should replicate the mediation analysis conducted in the current study while taking into account other eating disorders. Additional investigations of BN and

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its correlates must strive to improve the comprehension of these associations' pathways through designs that allow to draw temporal frameworks, in order to efficiently treat this eating disorder and prevent its negative outcomes.

Plain English summary

Bulimia nervosa, an eating disorder, is characterized by an impulsive consumption of food in a short period of time, followed by behaviors that compensate the eating such as vomiting or excessive exercise in order to avoid weight gain. Individuals with problematic social media use were found to have higher levels of bulimia symptoms. Symptoms of bulimia can also be associated with both depression and anxiety. The aim of the current study was to examine the mediating role of anxiety and depression between problematic social media use and bulimia nervosa. The results of our study found that problematic social media use was directly associated with more bulimia nervosa and also associated with higher depression and anxiety, both of which were associated with bulimia nervosa. Tackling associated disorders may help reduce symptoms of bulimia nervosa. Clinicians should carefully examine these associations while assessing and implementing treatment plans.

Keywords Bulimia nervosa, Anxiety, Depression, Problematic social media use, Lebanon

Introduction

The most severe mental illnesses affecting adolescents and young adults today are eating disorders (EDs), such as anorexia nervosa (AN), bulimia nervosa (BN), and binge eating disorder (BED) [1]. Worldwide, both males and females of all ages exhibit BN, which is linked to increased mortality risk [2]. BN is defined as "recurrent binge eating episodes along with inappropriate compensatory behaviors, and is linked to serious medical problems, mental comorbidity, and psychosocial impairment" [3]. People with BN may exhibit bursts of impulsive consumption of a lot of food in a short amount of time, followed by compensatory behaviors (such as excessive exercise, vomiting, laxative abuse, limited food intake) to prevent weight gain [4, 5]. In the systematic review of Galmiche et al., the lifetime prevalence rates of BN ranged from 0.1% to 1.3% in men and from 0.3% to 4.6% in women [6]. The peak age of incidence of BN ranged between 15 and 29 years [2]. In addition, compared to persons without an ED, all participants with EDs had greater median incomes and lower education [7]. A prior study conducted on EDs in Lebanon found that BN was the most prevalent ED (46.1%) ,followed by anorexia nervosa (39.4%) and binge eating (14.4%) [1]. Additionally, prior research revealed that 11.4% of university students in Lebanon had AN, BN, or BED diagnosis and that 21.2% were at risk for developing an ED [8]. ED behaviors are thought to be painful, as people are often engaged in extreme measures to alter body shape and abate concern about the body [9].

Body dissatisfaction is often used as a term to describe the body-related negative self-evaluation of an individual [10]. Body dissatisfaction was a strong prospective predictor of the severity of suicidal thoughts, and BN symptoms (binge eating and purging) predicted suicidal ideation [9]. When attempting to understand the emergence of body dissatisfaction and EDs, culture is a crucial factor to take into account since it determines the environment in which attitudes regarding the body are formed [11]. Lebanese media, similar to Western cultures, promotes the culture of "thinness" and "perfection" [12]. Lebanese are more susceptible to media messages encouraging them to eat less and exercise more in order to lose weight or gain muscle mass [13–18]. They also fear social criticism and are more susceptible to peer opinions. In addition, compared to their Cypriot peers, Lebanese women are more self-conscious about their body size [13].

EDs are multi-factorial and include biological, psychological, intrapersonal, and environmental influences. Exposure to media, one environmental factor, has been linked to the emergence of these problems and is probably mediated by thin-ideal internalization [19]. According to the biopsychosocial model, problematic social media use (PMSU) is characterized by the presence of addiction-like symptoms such as mood modifications (i.e., alterations in mood states with the excessive social media use), tolerance (i.e., an increase in the amount of time spent on social media), withdrawal symptoms (i.e., feeling contradicted or irritable when restricted from using social media), conflict (i.e., relationship problems as a result from using social media) and relapse (i.e., going back to social media use after stopping for a while) [20, 21]. Scales to assess Social Media Use as a type of addiction include several criteria of behavioral addictions such as: preoccupation, tolerance, withdrawal, persistence, displacement, problem, deception, escape and conflict [22, 23]. A previous research found a significant positive correlation between BN and the time spent on social networking

sites [24]. Furthermore, in two recent meta-analyses, Hinojo-Lucena and colleagues found that those with problematic use of internet had significantly higher rates of both EDs (AN, BN, and BED) and ED-related symptoms (food obsession, loss of control eating, and dieting) [25]. While aiming to examine an association between social media use and eating concerns, a study found a strong association between the two [19]. Social media is more widely available at young age; just one click can set off a range of ideas and behaviors that mimic EDs in those people, to conform to what society considers to be attractive [19]. With that being said, the pressure of media influence was associated with more EDs (restrained and emotional eating) among Lebanese undergraduates [26].

While many factors contribute to the development of BN, having a comorbid disorder can be associated with more severe symptoms of EDs [27, 28]. Godart and colleagues (2000) found that anxiety disorders were frequently present before the occurrence of EDs [29]. The results of a previous study suggested that the comorbidity of an ED with anxiety and depression was high [30]. An earlier network analysis study revealed that the anxiety symptoms of shakiness, unsteadiness, and dizziness were very central and closely related to the BN symptoms in the anxiety and BN network. Similarly, in the depression and BN network, the lack of interest in sex and changes in appetite were highly central [31]. Therefore, by identifying the core symptoms of the comorbid disorders (e.g., comorbid anxiety and depression symptoms), treatment of BN could be improved to concentrate on these symptoms. Anxiety positively contributed to addictive social networking, with social media use shown to be positively associated with depression among young adults [32, 33]. Depressive symptoms were also found to predict eating behaviors ten years later [34, 35]. A descriptive review found that the levels of neurocognitive alterations and impairment in individuals with AN were proportional to the severity of depressive symptoms [36]. It is noteworthy to also mention that depression can be secondary to EDs according to the results of a longitudinal study [37]. Similarly, anxiety moderated the association between body dissatisfaction and restrained eating; when levels of anxiety are high, body image dissatisfaction was more strongly associated with restrained eating [35]. Furthermore, depression moderated the association between body dissatisfaction and orthorexia nervosa [38].

As EDs are very uncommon in the general population, help seeking is frequently avoided or put off for many reasons, such as denial (especially in the case of AN) or stigma and shame (especially in the case of BN) [2]. Most of the epidemiological research on EDs has been conducted in Western nations. There is evidence to support the idea that non-Western nations are not immune to EDs where EDs are spreading, especially in the Middle East [1]. Mental health issues are frequently underestimated in developing countries, although they were shown to be prevalent in Lebanon following the COVID-19 pandemic [39], particularly in the context of a severe socio-economic crisis and political instability [40, 41]. Moreover, Arab cultures and mentalities favor and work hard for a thin and toned body, which puts a lot of pressure on people, therefore, emphasizing the importance of studying BN in these populations. In fact, the socio-cultural changes in the Arab countries have led to a shift from the admiration of curvy bodies to thin ones, a goal achieved by following ED behaviors [35, 42]. In view of the lack of previous studies that assess the correlates of BN in Lebanon, the aim of this study was to evaluate the mediating effect of anxiety and depression between PSMU and BN in a sample of Lebanese university students. We hypothesize that depression and anxiety may mediate the association between BN and PSMU, where an increase level of PSMU would be associated with higher levels of depression and anxiety, which would be associated with higher BN.

Methods

Study design and participants

This cross-sectional study was carried out between July and September 2021. A total of 363 university students was recruited through convenience sampling from several universities in Lebanon's governorates. Involved people were encouraged to visit a website that would guide them to the consent form, information form (purpose of the current study, anonymity, voluntariness of consent to research), and questionnaire. The data was collected online using the snowball technique in order to reach the target number. All participants responded willingly to the survey. There were no fees for participating in the study. All university students over the age of 18 were eligible to participate. Excluded were only those who refused to complete the survey and those who were not university students; no other exclusion criteria were applied [43].

Minimal sample size calculation

According to the G-power, a minimum of 316 students was deemed necessary to have enough statistical power, based on a 5% risk of error, 80% power, $f^2 = 2.5\%$ and 10 factors to be entered in the multivariable analysis.

Questionnaire and variables

The Arabic self-administered questionnaire with closed-ended questions was anonymous; the questionnaire required approximately 20 minutes to be completed. The questionnaire consisted of different sections. The first

part clarified socio-demographic characteristics: age, sex, marital status, and household crowding index. The latter, reflecting the socioeconomic status of the family, was calculated by dividing the number of persons in the house by the number of rooms in the house excluding the bathrooms and kitchen [44]. The physical activity index was calculated by multiplying the intensity by the frequency by the time of physical activity [45].

The second part of the questionnaire included the following scales:

Eating attitude test (EAT-26)

The EAT, validated in Lebanon in Arabic [46, 47], was used to assess disordered food attitude. The questionnaire comprises twenty-six questions each with six response options, varying from infrequently/almost never/never (0) to always [3]. It is divided into three subscales: dieting (avoidance of fatty foods and preoccupation with thinness), bulimia and food preoccupation, and oral control (self-control over food and social pressure to gain weight). The total score was calculated by summing all questions answers and can vary from 0 to 78. A score of 20 or above indicates possible disordered food attitudes. In this study, only the bulimia subscale was used. The bulimia scale included items such as: "I vomit after I have eaten". The Cronbach's alpha in this study was 0.87.

Body dissatisfaction subscale of the eating disorder inventory-second version (EDI-2)

The body dissatisfaction subscale evaluates the degree of dissatisfaction to the overall body, and to particular body element. It is made of nine items (i.e., "I am satisfied with the shape of my body"), scored on a 4-point Likert scale, from never (0) to always [3]. Higher scores correspond to a higher level of body dissatisfaction [48]. The Arabic version of the scale was used in a previous study [49]. The Cronbach's alpha in this study was 0.60.

Social media disorder scale (SMD)

Validated in Lebanon in Arabic [50], the short form of the SMD was used in this study. It is composed of 9 items (i.e. "Over the last year, have you often felt bad when you when you could not use social media?"), with higher scores reflecting more problematic social media use [22]. The Cronbach's alpha in this study was 0.79.

Lebanese anxiety scale (LAS-10)

Lebanese Anxiety Scale (LAS-10) is a 10-item instrument in Arabic measuring the severity of anxiety symptoms among Lebanese adults [49] and adolescents [50]. This scale was previously used in Lebanon [51, 40]. In LAS-10, the first seven questions are graded from 1 to 10, and the last three questions are graded from 1 to 4 based on the repetitive manifestation of symptoms (i.e., "I feel that the difficulties are accumulating to the point where I can't get through them"). Higher scores indicate higher anxiety levels. The Cronbach's alpha in this study was 0.89.

Patient health questionnaire (PHQ-9)

The PHQ-9 is a 9-item self-report scale (i.e. "Over the past two weeks, how often have you been bothered by the following: little interest or pleasure in doing things"), previously validated in Lebanon in Arabic [52], which is used to assess and check the severity of depression. PHQ-9 total score ranges from 0 to 27, with a cut-off point of 0–4 indicates no depressive symptoms, 5–9 mild depressive symptoms, 10–14 moderate depressive symptoms, 15–19 moderately-severe depressive symptoms, and 20–27 severe depressive symptoms [53]. The Cronbach's alpha in this study was 0.90.

Statistical analysis

SPSS software version 25 was used to conduct data analysis. The normality of the BN score was verified via the skewness and kurtosis values varying between -1 and +1 [54]. A bivariate analysis using the Pearson correlation test served to assess the relationship between the BN score and other continuous variables, whereas the Student t test was used to compare two means. A linear regression was conducted taking the BN score as the dependent variable. The PROCESS SPSS Macro version 3.4, model four [42] was used to test the indirect effect and calculate three pathways. Pathway A determined the regression coefficient for the effect of PSMU on mental health issues (depression/anxiety); Pathway B examined the association between mental health issues on BN, and Pathway C' estimated the direct effect of PSMU on BN. Pathway AB was used to calculate the indirect effect of PSMU on BN via depression/anxiety. A serial mediation analysis was conducted afterwards to test the mediating effect of depression and anxiety consecutively in one model. An indirect effect was deemed significant if the bootstrapped 95% confidence intervals of the indirect pathway AB did not pass by zero [42]. The linear regression and moderation analysis were adjusted over all variables that showed a $p<0.25$ in the bivariate analysis. Significance was defined at $p<0.05$.

Results

Sociodemographic and other characteristics of the participants

A total of 363 students participated in this study; their mean age was 22.65 ± 3.48 years (min = 18; max = 37), with 61.7% females. The mean BN score was 3.10 ± 4.29. Other characteristics are summarized in Table 1.

Table 1 Sociodemographic and other characteristics of the participants (N = 363)

Variable	N (%)
Sex	
Male	139 (38.3%)
Female	224 (61.7%)
Marital status	
Single	343 (94.5%)
Married	20 (5.5%)
	Mean ± SD
Age (in years)	22.65 ± 3.48
Body mass index (kg/m^2)	23.62 ± 4.13
Physical activity index	27.94 ± 20.44
Household crowding index (person/room)	1.01 ± 0.53

SD = Standard Deviation

Moreover, 122 (33.6%) of the participants had eating disorders (EAT scores of 20 or more).

Bivariate analysis

The bivariate analysis results are summarized in Tables 2 and 3. Older age (r = − 0.11) was significantly associated with less BN, whereas higher PSMU (r = 0.31), higher body dissatisfaction (r = 0.16), higher anxiety (r = 0.48)

Table 2 Bivariate analysis of the categorical variables associated with bulimia.

Variable	Bulimia			
	Mean ± SD	*p*	Effect size	Statistical test used
Sex		0.223	0.130	Student t test
Male	2.76 ± 3.92			
Female	3.31 ± 4.50			
Marital status		0.833	0.052	Student t test
Single	3.11 ± 4.32			
Married	2.90 ± 3.71			

Numbers refer to mean ± SD

Table 4 Multivariable analysis: Linear regression (using the ENTER model) taking bulimia as the dependent variable.

	Beta	β	*p*	95% CI
Age	0.01	0.01	0.867	−0.10; 0.12
Body Mass Index	−0.03	−0.03	0.536	−0.14; 0.07
Physical activity index	0.01	0.05	0.246	−0.01; 0.03
Body dissatisfaction	0.18	0.32	**< 0.001**	0.12; 0.24
Problematic Social media use	0.26	0.14	**0.002**	0.10; 0.43
Anxiety	0.16	0.31	**< 0.001**	0.10; 0.23
Depression	−0.01	−0.02	0.754	−0.10; 0.07

*Reference group; Beta = unstandardized beta; β = standardized beta; CI = Confidence interval; numbers in bold indicate significant *p*-values. Nagelkerke R^2 = .337

and higher depression (r = 0.36) were significantly associated with more BN.

Multivariable analysis

A linear regression taking BN as the dependent variable, showed that higher PSMU (Beta = .26), higher anxiety (Beta = .16) and higher body dissatisfaction (Beta = .18) were significantly associated with more BN (Table 4).

Mediation analysis

The results of the mediation analysis (adjusted over age, sex, BMI, physical activity, body dissatisfaction) showed that depression and anxiety partially mediated the association between problematic social media use and BN (Table 5). Higher problematic social media use was significantly associated with more depression/anxiety, whereas more depression/anxiety was significantly associated with more BN. Finally, higher problematic social media use was directly and significantly associated with more BN (Figs. 1 and 2).

Table 3 Correlation matrix of continuous variables.

	1	2	3	4	5	6	7	8	9
1. Bulimia	1								
2. Age	−0.11*	1							
3. Body Mass Index	0.07	0.29***	1						
4. Physical activity index	0.07	−0.13*	−0.08	1					
5. Household crowding index	0.02	−0.12*	0.02	0.02	1				
6. Problematic Social media use	0.31***	−0.18***	−0.06	0.001	0.07	1			
7. Body dissatisfaction	0.16**	0.08	0.07	0.03	0.01	0.17**	1		
8. Anxiety	0.48***	−0.19***	−0.05	0.10	0.06	0.32***	0.13*	1	
9. Depression	0.36**	−0.16**	−0.02	0.03	0.12*	0.32***	−0.07	0.69***	1

*p <.05; **p <.01; ***p <.001; numbers refer to Pearson correlation coefficients.

Table 5 Mediation analyses results, taking problematic social media use as the independent variable, depression/anxiety as the mediators and bulimia as the dependent variable

Mediator	Direct effect			Indirect effect		
	Beta	SE	*P*	Beta	Boot SE	Boot CI
Depression	0.34	0.09	<0.001	0.18	0.05	0.10; 0.29*
Anxiety	0.32	0.09	<0.001	0.21	0.05	0.13; 0.31*

*Indicates significant mediation

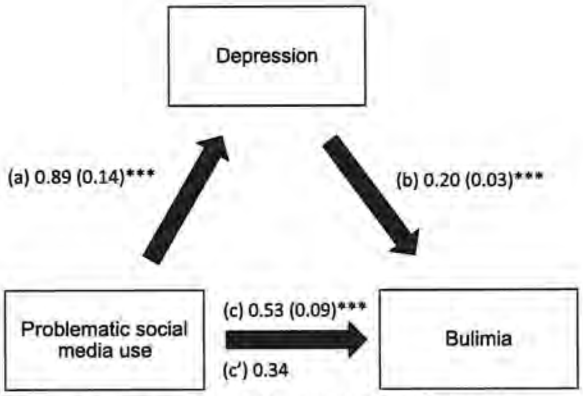

Fig. 1 **a** Relation between problematic social media use and depression (R2 = .133); **b** Relation between depression and BN (R2 = .209); **c** Total effect of problematic social media use and BN (R2 = .130); **c'** Direct effect of problematic social media use and BN. Numbers are displayed as regression coefficients (standard error). ***$p < 0.001$

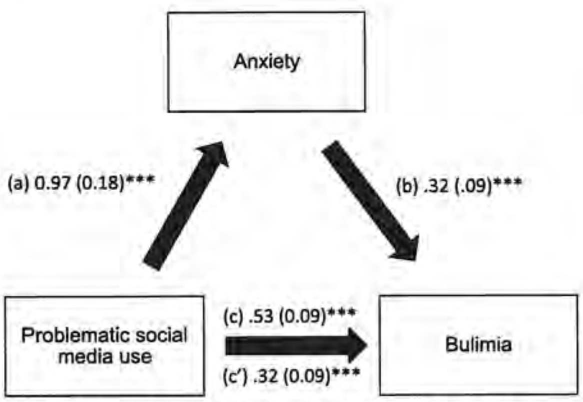

Fig. 2 **a** Relation between problematic social media use and anxiety (R2 = .132); **b** Relation between anxiety and BN (R2 = .279); **c** Total effect of problematic social media use and BN (R2 = .130); **c'** Direct effect of problematic social media use and BN. Numbers are displayed as regression coefficients (standard error). **$p < 0.01$; ***$p < 0.001$

Serial mediation

The mediation analyses were conducted following the indirect effect key below:

Indirect effect 1: PSMU → Depression → Bulimia
Indirect effect 2: PSMU → Anxiety → Bulimia
Indirect effect 3: PSMU → Depression → Anxiety → Bulimia

The results of the mediation analysis (adjusted over age, sex, BMI, physical activity, body dissatisfaction) showed that depression and anxiety mediated the association between problematic social media use and BN (Table 6). When entering anxiety (M1) then depression (M2) as consecutive mediators in Model 1, the results showed that only depression mediated the association between PSMU and bulimia. When taking depression (M1) then anxiety (M2) as consecutive mediators, the results showed that the mediation PSMU → Depression → Anxiety → Bulimia was significant. Higher PSMU was significantly associated with more depression, which was significantly associated with more anxiety, which was significantly associated with more bulimia. Finally, higher PSMU was directly and significantly associated with more bulimia (Fig. 3).

Discussion

The aim of the current study was to examine the mediating role of depression and anxiety between PSMU and BN among a sample of Lebanese university students. Higher levels of PSMU, anxiety and body dissatisfaction were all correlated with BN. Depression and anxiety partially mediated the association between problematic social media use and BN. When entering anxiety then depression as consecutive mediators, the results showed that only depression mediated the association between PSMU and bulimia. When taking depression then anxiety as consecutive mediators, the results showed that the mediation PSMU → Depression → Anxiety → Bulimia was significant.

PSMU, depression and anxiety

In a study conducted on 456 Lebanese residents, 107 (23.7%) were classified as having a social media use disorder [55]. The time spent on smartphone screens increased during the COVID-19 pandemic and lockdowns [56] and was associated with more insomnia [57]. The fear of

Table 6 Indirect effect analyses results, taking problematic social media use as the independent variable, depression and anxiety as consecutive mediators and bulimia as the dependent variable

	Direct effect			Indirect effect		
	Beta	SE	*p*	Beta	Boot SE	Boot CI
Model 1: anxiety then depression as consecutive mediators.						
Total	0.31	0.09	<0.001	0.22	0.05	0.13; 0.33*
Indirect effect 1				0.20	0.05	0.10; 0.31*
Indirect effect 2				0.01	0.02	−0.03; 0.07
Indirect effect 3				0.01	0.03	−0.04; 0.07
Model 2: depression then anxiety as consecutive mediators						
Total	0.31	0.09	<0.001	0.22	0.05	0.13; 0.33*
Indirect effect 1				0.02	0.05	−0.07; 0.13
Indirect effect 2				0.04	0.04	−0.03; 0.12
Indirect effect 3				0.16	0.04	0.09; 0.25*

*Indicates significant mediation.

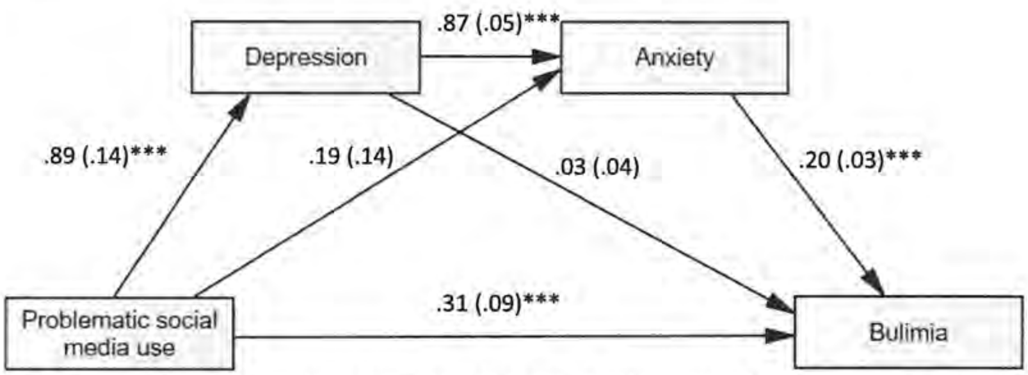

Fig. 3 Serial mediation of the effect of problematic social media use on bulimia, taking depression and anxiety as consecutive mediators; ***$p < 0.001$

COVID-19 and the lockdown's impact were both associated with lower general wellbeing, anxiety and depression among Lebanese samples [58, 59]. Results of our study showed that higher PSMU was significantly associated with depression and anxiety, in line with previous findings [60–62]. These authors speculated that the reason for this association may be due to the fact that individuals who engage in online-activities in an excessive way, may neglect healthy aspects of their lives, which could contribute to depressive symptoms. Hence, excessive internet users may more be likely to replace their real-life interactions by online sites than the normal users. They were also found to have more depressive symptoms [61, 62]. A study conducted on Lebanese university students had found a significant association between potential internet addiction and insomnia, depression, anxiety and stress [63]. Moreover, a systematic review of 159 articles, found a bidirectional relationship between PSMU and depression and anxiety; depressed or anxious people may have a higher use of social media, whereas those using social media intensely or excessively may report greater depression or anxiety. The authors of this systematic review concluded that depression and anxiety can be both the causes and consequences of PSMU [64]. In an attempt to evaluate the association between PSMU and its correlates, a Lebanese study found an association between PSMU and anxiety and social phobia [65], in agreement with other international studies [66, 67]. PSMU was associated with an increased level of loneliness, where individuals presenting depressive symptoms may be more prone to use social media rather than face-to-face interactions [68–70]. Adolescents who spend less time in front of their screen and engage in more physical activities were found to have lower risks of reporting mental health problems [71].

Depression, anxiety and BN

Higher depression and anxiety were both associated with higher BN in the current study, consistent with the findings of a previous study [31]. These authors have found

that dizziness, unsteadiness, alterations in appetite and lack of sex were central in BN. Furthermore, 65% of women presenting for treatment of an ED also met the criteria for at least one comorbid anxiety disorder [30]. Previous authors demonstrated that, in addition to distorted body-related thoughts, maladaptive self-evaluative perfectionism - which has been linked to core components of social anxiety disorder – mediated the relationship between bulimic symptoms and social interaction anxiety and fear of public scrutiny, two significant components of social anxiety disorder [72]. As hypothesized by Mitchell and colleagues, the two most common comorbid disorders in BN, generalized and social anxiety, could lead patients with BN to develop an interest in their body weight and shape [73]. Individuals presenting depressive symptoms showed significantly higher symptoms of BN than those without a diagnosis of depression [74]. Improving adherence to and results of ED interventions remain significant priorities for patients with comorbid anxiety disorders as they typically have worse illness courses and outcomes [75]. One symptom that was found to bridge the association between depression, anxiety and BN was physical sensation, which explains how these three disorders may interact [31].

PSMU and BN

Our study results revealed that higher PSMU was directly associated with more BN, corroborating the results of a previous study [19]. One reason for the study's findings is that people who use social media more frequently are exposed to more pictures and messages that increase the chances of developing ED. The posting and viewing of images and videos are particularly prevalent on some social media platforms, including Instagram, Snapchat, Pinterest, and Tumblr [16, 19]. In Lebanon, the number of social media users at the start of 2022 was equivalent to 75.2% of the total population [76]. Users of social media platforms could be exposed to powerful visual content, such as images that might support the slender ideal [19]. On top of that, it is believed that Western media content and exposure has been shown to significantly affect body image and eating behavior by promoting a "culture of thinness", predicting disordered eating symptoms, body dissatisfaction and a drive to thinness in women [77]. This exposure to thin-ideal images culture was positively associated with body dissatisfaction, food restriction and ED symptoms, which may contribute to EDs [77, 78]. With the spread of social media use and network sites, this increase in the drive to thinness and body dissatisfaction could make teenagers and young adults more vulnerable to EDs, while playing a primordial role in disordered eating attitudes [79, 80]. To our knowledge, this is the first study that aimed to evaluate the mediation effect of depression and anxiety between BN and PSMU. Anxious and depressive temperaments as well as state anxiety, had a direct unmediated effect on the drive to thinness, which is a core body-related psychopathology of AN [81].

Body dissatisfaction and BN

The results of the current study showed a positive association between body dissatisfaction and BN, which is consistent with previous findings [82]. Individuals with higher levels of body dissatisfaction usually have higher levels of abnormal eating attitudes such as drive for thinness or fear of gaining weight [83], which lead researchers to identify body dissatisfaction as a risk factor for EDs [84].

Clinical implications

The findings of this study may help clinicians better understand the associated factors – depression, anxiety and PSMU that increase BN symptoms. They may serve as a first step to create early intervention strategies, such as Cognitive Behavior Therapy – Enhanced (CBT-E), which was proven to have an important impact on the reduction of EDs symptoms [85, 86]. As anxiety and depression were positively associated with BN, reducing their levels may in turn be associated with a decrease in BN levels; hence, other forms of treatment that tackle depression and anxiety may also be of use to reduce BN symptoms such as Cognitive Behavioral Therapy [87, 88], Schema Therapy [89], and Mindfulness-Based Interventions [90]. The need for campaigns and awareness about the harms of PSMU would also be needed in Lebanon.

Strengths and limitations

There are some limitations in our study. The data's cross-sectional nature limits the ability to pull causality conclusions. The use of a self-administered questionnaire and the under or over-estimation of a question pose a risk for information bias. There is also a risk of selection bias, given the nature of the sample enrollment and the fact that we cannot know the refusal rate. Furthermore, a residual confounding is still possible, despite the fact that we included several factors as potential confounders. Recruitment was completed entirely online due to security and health reasons in Lebanon. Moreover, it is recommended to conduct longitudinal or cross-sectional studies taking into consideration the association between time spent on SM and other variables while taking into consideration the content consumed while using social media. Although validated in Lebanon, the SMD scale was created to screen for the possible problematic social media use in participants but not for diagnosis, since

social media is not yet classified as an addiction or disorder according to the DSM-5.

Notwithstanding these limitations, the results represent preliminary evidence and could be considered as a baseline for future studies to investigate other variables associated with PSMU and BN in Lebanon. This study revealed important findings that encourage further exploration of BN and its correlates in Lebanon.

Conclusion

BN is a serious mental and physical illness that involves complex and damaging relationships with food, eating, exercise, and body image. Improved awareness might lead to earlier detection and treatment in these groups that suffer from an extra stigma of a 'young, Western, female-specific' psychiatric disorder. Additional investigations of BN and its correlates must strive to improve the comprehension of these associations' pathways through designs that allow drawing temporal frameworks, in order to efficiently treat this ED and prevent its negative outcomes. Futures studies should replicate the mediation analysis conducted in the current study, while taking into account EDs other than BN.

Abbreviations

BN	Bulimia nervosa
PSMU	Problematic social media use
ED(s)	Eating disorder(s)
AN	Anorexia nervosa
BED	Binge eating disorder

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Author contributions

SO and SH designed the study; CR and MS drafted the manuscript; SH carried out the analysis and interpreted the results; all authors reviewed the final manuscript and gave their consent. All authors read and approved the final manuscript.

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Availability of data and materials

All data generated or analyzed during this study are not publicly available due the restrictions from the ethics committee.

Declarations

Ethics approval and consent to participate

The Psychiatric Hospital of the Cross Ethics and Research Committee approved this study protocol (HPC-007-2021). Submitting the form online was considered equivalent to obtaining a written informed consent. All methods were performed in accordance with the relevant guidelines and regulations.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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Filtering the reality: Exploring the dark and bright sides of augmented reality–based filters on social media

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Abstract

The study aims to investigate the effect of augmented reality (AR)-based filters on social media users' self-concept and well-being. While much research has explored consumer use of AR filters and their effect on buying behaviour, few studies have examined how such filters affect self-concept, especially in the context of social media use (rather than retailing). We used the inductive qualitative method and grounded theory to analyse 18 AR filter users' in-depth interviews. We found that using AR filters broadens the gap between the actual self and the ideal self, intensifying the social comparison process. On the positive side, some users may get inspired to reduce the ideal-actual gap through the creative use of the AR tools available. However, on the negative side, other users may feel negative emotions like envy. These positive and negative feelings may affect the user's body satisfaction and self-confidence, ultimately changing their usage intention.

JEL Classification: M31

Keywords

AR filters, augmented reality, self-concept, social comparison, social media, well-being

1. Introduction

> '*People are creating a new AR version of themselves every day on social media. They are trying their level best to change their realities*'. *(#R14, female, 26)*

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With the ubiquitous presence of smartphones in modern society, the term 'selfie' has emerged as a pervasive term, capturing the attention of the masses. Such was its impact that in 2013, the Oxford Dictionary recognised it as the 'word of the year'. However, the advent of augmented reality (AR) has fundamentally transformed the selfie concept, offering a disruptive new approach. Unlike traditional photo editing and visual enhancements through static filters, AR filters offer a dynamic, interactive experience that enables real-time manipulation and engagement. AR as a medium integrates virtual content realistically into a user's field of view (Flavián et al., 2019; Rauschnabel et al., 2022b). Prominent brands and firms such as Mini, IKEA, Zara, Lens Kart and Sephora have introduced AR-based virtual try-on apps. However, the most widespread use of AR is in social media (Kumar, 2021), where users use AR filters for selfies, videos and pictures. Research in this domain, however, has been scarce.

In recent years, leading social media platforms such as Instagram, Facebook and Snapchat have embraced AR filters that were initially introduced for entertainment and enjoyment. However, these filters have now evolved to become a powerful tool for image enhancement, as highlighted by prior research (Cowan et al., 2021; Fox et al., 2018; Javornik et al., 2021). By enabling users to enhance features such as their eyes, cheekbones, eyelashes and skin, AR filters have opened up a world of possibilities for individuals seeking to present themselves in a certain light. Moreover, users can also create their filters for public use, further expanding the potential impact of this technology. The popularity of AR filters is reflected in the staggering number of daily pictures created on Snapchat, which exceeds five billion (Backlinko, 2021). As AR filters have continued to evolve and improve, their ability to enhance images has reached new heights, providing users with even greater flexibility and creativity in their self-expression. As they do so, the continued use of AR filters on social media progressively blurs the boundaries between reality and illusion. The subsequent impact on users could illustrate both a bright and a dark side (Javornik et al., 2022; Ibáñez-Sánchez et al. (2022). In addition, the emergence of social media as a popular interaction and entertainment tool has changed how people present themselves in their peer networks (Andreassen et al., 2017). However, there is a dearth of research on the social and psychological outcomes of such social media-based innovations (e.g. AR) (Testa et al., 2020).

The majority of existing marketing literature on the use of AR filters focuses on consumer psychology, that is the role of AR filters on purchase intentions in the retail sector. However, research exploring the connection between AR filters and the self-concept remains under researched. Following the call by Kumar (2021) and Javornik et al. (2021) to investigate AR's influence on self-concept and explore both the social, bright and dark sides of AR, we started with the broad objective of trying to understand how the use of AR filters on social media could affect the self-concept and well-being of users.

More specifically, social media platforms provide several AR features, such as face filters, virtual backgrounds and avatars, allowing users to self-express themselves and exchange creative communication, triggering psychological and emotional responses (Chua and Chang, 2016). Using filters and showing a better version of oneself has become customary. However, we still know very little about how the regular use of such filters influences users' self-concept and feelings of well-being or their behavioural intentions like continued usage (Javornik et al., 2021; Kumar, 2021; Trifiro, 2018). This curiosity was the initial trigger for this research.

Theoretically, we attempt to extend the literature beyond the technical aspects of AR and focus on its felt aspects by analysing the lived experiences of a group of users. We draw upon social comparison theory and self-concept theory to explain AR's influence on well-being and the usage intentions of social media apps. Such qualitative analyses can provide a foundation for building propositions for future research. From the practitioner's standpoint, social media is a prime platform for promotion and many companies use AR ad lenses (camera effects that add AR elements

to photos/environment in real time) as a promotional tool. Therefore, the study may help them design their ad lenses for better brand attachment and engagement through improved user psychology understanding. The following section discusses the theoretical background and the research gaps, followed by the methodology section. Finally, we present the findings, discussion and avenues for future research.

2. Theoretical background

2.1. Self-concept and self-discrepancy theory

Self-concept is the total of an individual's thoughts and feelings about herself (Rosenberg, 1965). Researchers have also distinguished between multiple dimensions of self-concept. Although the specific aspects of self-concept examined vary from researcher to researcher, most distinguish between *actual* self-concept,; defined by the qualities and attributes that a person (and others) believes that they possess (Higgins, 1987), and the *ideal* self-concept, that is how a person perceives how they would ideally like to be, which includes the qualities that they may wish to possess, but currently lack (Fox et al., 2018; Higgins, 1987; Onkvisit and Shaw, 1987; Sirgy, 1982).

The self-discrepancy theory proposed by Higgins (1987) suggests that the ideal self-concept forms a sort of 'self-guide' (p 320) and that people are constantly motivated to reach the point where their actual self-concept matches the self-guide. Moreover, self-concept can arise from many facets of oneself, including intelligence, attractiveness, occupation or other general abilities (Markus and Nurius, 1986). Since the sample of interest here was defined as users of AR filters on social media, it would be safe to assume that physical attractiveness would be salient to the self-concept. Therefore, we may expect the ideal-actual attractiveness gap (Javornik et al., 2021) to be a salient concept in our context. For the purpose of simplicity, in the rest of this article, we will refer to the 'ideal-actual gap' as implying the gap between the ***ideal*** standard of attractiveness and the self-perceived level of ***actual*** attractiveness.

Further, self-image relates to well-being in the context of social media in terms of both positive feelings like life satisfaction and happiness and negative feelings like boredom, anxiety and depression (Javornik et al., 2021; Weinstein, 2018). Therefore, we may expect the ideal-actual attractiveness gap to be associated with feelings of well-being in our sample. It is of interest to examine how these processes play out in our research context, where manipulation of the self is common.

2.2. Augmented reality

Milgram and Kishino (1994) proposed the reality-virtuality continuum, where real and virtual environments exist at opposite poles. The real environment includes the reality itself, whereas the virtual environment includes a completely computer-generated environment. In addition, mixed reality (MR) included any place wherein the real and virtual elements were presented in a single display, thereby defining AR and augmented virtuality (AV) as part of MR. However, with the rapid technological evolution and increasing power of technological devices in terms of their immersive experience, the Milgram and Kishino (1994) continuum was extended by Flavián et al. (2019), who provided a new and refined continuum, adding pure MR between AR and AV. The authors posited that in pure MR, the users are placed in the real world wherein the digital content is completely integrated into their surrounding environment, thus allowing them to interact with both digital and real content, and these elements can also interact. While acknowledging different definitions of (pure) MR (e.g. Flavián et al., 2019; Milgram and Kishino, 1994), we focused on the xReality theory proposed by Rauschnabel et al. (2022b) that asserts that AR and VR could be two

concepts under the umbrella term XR, where AR ranges from assisted to MR based on the level of local presence. In contrast, VR ranges from atomistic to holistic VR based on the level of telepresence. Therefore, AR integrates virtual content realistically into a user's field of view, ranging from very functional uses (assisted reality) to highly realistic experiences (MR) where virtual elements are almost indistinguishable from real ones' (Rauschnabel et al., 2022b).

The unique characteristics of AR, such as its first-person perspective, concreteness, accuracy and immediacy, distinguish it from other forms of retail media, such as web and social media (Kumar et al., 2023a, 2023b). Therefore, the conclusions drawn from previous studies cannot be extrapolated to the context of AR (Huang, 2021; Kumar and Srivastava, 2022; von der Au et al., 2023). In addition, AR content is commonly perceived as possessing greater levels of enjoyment (Mishra et al., 2021), inspiration (Zanger et al., 2022), interactivity (Yim et al., 2017), engagement (Jessen et al., 2020) and immersion (Hilken et al., 2017; Trunfio et al., 2022) in comparison to conventional presentation formats. Therefore, findings from other media formats literature can may not be generalisable to the AR context.

Particularly in the social media context, AR filters add a transformative layer of immersive technology that alters users' perceptions of reality (Javornik et al., 2022). In contrast, traditional social media research focuses primarily on user interactions, content generation and dissemination patterns. In addition to altering the visual aesthetics, these filters significantly impact user engagement, content virality and the overall user experience (Flavián et al., 2021). Thus AR filters challenge our preconceived conceptions of online self-representation by allowing users to reimagine their online personas in novel and interesting ways. As a result, the study of AR filters necessitates a multidisciplinary approach that considers human cognition, technological advancements and altering digital communication paradigms, making it a more complex and richer field than social media analysis.

2.3. AR and self-concept

Among many use cases for AR, social media AR filters have become increasingly popular. As users create and consume such widely shared content consisting of artificially enhanced 'selfies's, ideas of what constitutes attractiveness (the ideal self) and how they and others perceive them (the actual self) may change and distort, leading to negative consequences like social media addiction and reduced life satisfaction (Fastoso et al., 2021). Given the widespread adoption of AR filters on social media, we found very few studies exploring how the continued use of these filters could affect the self-concept and well-being of social media users.

A small body of literature on AR and self-concept exists in the context of virtual try-on in the retail sector (Javornik et al., 2021; Scholz and Duffy, 2018; Yim and Park, 2019). However, such studies have mostly focused on the impact of AR on purchase behaviours or consumer experience (Flavián et al., 2021; Javornik, 2016; Yim and Park, 2019). In most of these studies, self-related factors like psychological ownership, self-esteem, body surveillance or favourable body images have been incorporated in the (mostly) quantitative models as boundary conditions. For example, Huang et al. (2019) considered body surveillance (one's proneness to see their body as something to be admired and judged by others) as a moderating the relationship between AR virtual try-on on the consumer rapport experience in online retailing. However, the authors do not look at AR's effect on body surveillance or its proximal and distal outcomes. Similarly, Yim and Park (2019) investigated consumers' responses to AR product presentations. The authors found that body image moderated the relationship between AR attributes (interactivity and media irritation) and adoption intention. In short, users with unfavourable body images will find AR more useful. Therefore, in treating self-concept-related variables as boundary conditions in the relationship between AR use

and consumer behaviour, these studies have not addressed the direct effect of AR use on users' psychology.

We further contend that the user's primary purpose of using AR marketing stimuli for shopping (purchase) differs greatly from the purpose of using AR on social media (interaction and self-expression). Hence, the phenomena are likely to involve a different set of feelings, attitudes and behaviours. In this research, our focal context is the social media user, and our focal concept is the self-concept.

We could find very few studies examining AR filters' influence on the self-concept. Some recent exceptions by Javornik et al. (2021, 2022) and Ibáñez-Sánchez et al. (2022) have discussed some of these phenomena in detail. We try to build on this small body of literature in the following ways.

First, the current study extends previous research on the following points (1) the primary focus of Javornik et al. (2022) was on the *motivations* for using AR filters. In contrast, the current study focuses on the *effect* of using AR filters. (2) While Javornik et al. (2022) represent psychological well-being through self-acceptance and positive affect, the current study tries to capture actual user well-being experiences through qualitative interviews. Thus, we move the focus away from motives for using AR filters towards a richer understanding of its effect.

Second, Ibáñez-Sánchez et al. (2022) are one of the few researchers who examine the use of AR filters in the context of social networks; however, again, the focus is on understanding why people use AR filters rather than on understanding the impact of such use on the user psychology. Specifically, Ibáñez-Sánchez et al. (2022) do not offer any insights into how the usage of AR filters influences the self-concept and well-being of users, which is the primary focus of the current study.

Third, Javornik et al. (2021) introduced the concept of augmented self in the physical retailing (rather than social media) context by contending that use of AR mirrors influences ideal-actual gap. However, the article does not focus on how AR influences the ideal-actual gap and the user's response to it. Thus, a literature review revealed scant research on the effect of AR use on self-concept (Javornik et al., 2021, 2022), especially in the context of social media (Fastoso et al., 2021; Kumar, 2021).

Therefore, we conclude that:

1. While use of AR filters has changed the way people interact, communicate and project themselves on social media, its influence on users' self-concept and individual well-being remains under-researched.
2. Scholarly inquiry has mainly focused on the impact of AR filters on consumer behaviour (usage intention) in the retail sector or on users' motivations to use AR filters rather than the effect of AR filters on users in social media. Moreover, usage intention through the self-concept lens has not got much attention.

According to BCG (2018), 120 million Americans will engage with AR filters monthly in 2022. Thus, (i) there is likely to be an exponential growth in the number of users of AR filters worldwide, (ii) the use of AR filters can have a significant influence on the self-concept and (iii) face filters are the main reason for continuous usage of AR-based social media platforms like Snapchat and Instagram (PEW Research, 2021).

Against the backdrop, the purpose of this research is to explore the following:

1. How does the use of AR filters shape the self-concept and well-being of social media users?
2. How does the use of AR filters shape the usage intention behaviour of social media users?

The authors use an inductive, qualitative approach to explore the above research questions, using in-depth interviews with AR-based social media users.

3. Methodology

Since the purpose of the study is exploratory in nature and there is inadequate literature available, that warrants a qualitative approach. A qualitative method would allow a richer understanding of abstract and under-explored concepts like ideal/actual self-concept and well-being. Grounded theory is deemed appropriate to explore 'how' and 'why' types of questions and facilitates the exploration of new issues (Strauss and Corbin, 1994). It follows an inductive approach with rich data collected firsthand, leading to theory construction (Charmaz, 2008). Given the nature of our research questions, we adopted Charmaz's (2008) interpretive approach since we felt that it was essential to understand the feelings and experiences of participants while being aware of our own interpretation of the data. Several researchers have similarly used grounded theory to understand the self-concept in the social media setting (Nguyen et al., 2020; Tanwar, 2020) as our understanding of advanced social media tools continues to change and evolve.

3.1. Data and method

Following Charmaz (2008) for the sampling procedure, we interviewed millennials and Gen Z respondents who had used Snapchat, Instagram or both for more than one year in India. We specifically choose only those who have used AR filters extensively over the past 1 year. Next, for the context, we choose India because India has the second-largest Snapchat user base after the USA, consisting of 99.8 million users. It ranks no.1 on Instagram, with over 180 million users (Statista, 2021). Within India, data was collected from Delhi and the national capital region (NCR). NCR is one of the highest contributors to the national GDP and is highly cosmopolitan, with a resident population representing diverse regions of India. We used students as the target sample since Snapchat and Instagram are the most popular among the 18–24 age group, with 71% of the people in the age group using these platforms (Backlinko, 2021). In addition, students are more exposed to new technologies such as AR and prefer to shop online (Junco et al., 2010). Studying student samples in AR marketing is an established procedure (for more details, see Kowalczuk et al., 2021; Rauschnabel, 2018, Rauschnabel et al., 2019), and the homogeneity of the sample increases the internal consistency of research findings. Furthermore, using student samples is appropriate for exploring the self-concept concerning social media platforms (Instagram, Snapchat) (See Fox et al., 2018); students are prime users of social media.

As discussed above, respondents were selected based on their use of AR filters on Snapchat and Instagram. The demographic profile is presented in Table 1. The average age of our participants was 23 years. All except 4 of our research participants were 24 or younger and represented Generation Z, primarily digital natives (Dimock, 2019). The others represent millennials. We used a theoretical sampling procedure to enhance the study's analytical power. In the theoretical sampling procedure, the data is collected till data saturation, that is when no new concept emerges from the data (Glaser and Strauss, 1967). After the 14th interview, we achieved data saturation. We further interviewed 4 participants to ensure that no new themes emerged from further interviews. We reached theoretical saturation according to the grounded theory protocol (Charmaz, 2008).

3.2. Interview process

Due to the COVID-19 pandemic, we interviewed people telephonically and through video conferencing via Google Meet. Interviews were conducted between 3 June 2021 and 17 July 2021. We used semi-structured interviews and modified the interview protocol in the process. We

Table 1. Demographic profile.

Participant number	Gender	Age	Occupation	Overall perception of AR filters
#R1	Female	22	Undergraduate student	Positive
#R2	Female	24	Postgraduate student	Negative
#R3	Male	21	Undergraduate student	Positive
#R4	Female	27	PhD scholar	Positive
#R5	Male	22	Undergraduate student	Negative
#R6	Male	35	Assistant professor	Positive
#R7	Female	24	Postgraduate student	Positive
#R8	Male	19	Undergraduate student	Negative
#R9	Female	18	Undergraduate student	Negative
#R10	Male	22	Undergraduate student	Positive
#R11	Female	23	Postgraduate student	Positive
#R12	Female	24	Postgraduate student	Negative
#R13	Male	20	Undergraduate student	Positive
#R14	Female	26	Undergraduate student	Negative
#R15	Female	22	Undergraduate student	Positive
#R16	Male	25	Postgraduate student	Positive
#R17	Female	21	Undergraduate student	Negative
#R18	Male	23	Undergraduate student	Positive

AR: augmented reality.
All the participants had a prior experience (>1 year) of using AR filters on Snapchat and Instagram.

completed the interview process in three phases. In the first phase, we interviewed four participants, recorded the interviews, manually transcribed them and coded them. Initially, we identified the ideal-actual gap and body dissatisfaction as prominent themes. The outcomes were discussed among authors at each stage of the interview process to bring more comprehensiveness to the theorising process. In the second phase, we further interviewed 7 participants, wherein we found social comparison and inspiration as additional themes and the rest were interviewed in the last phase. The basic questions to start the interview process were 'What social media platforms do you use and why?', 'How often do you use AR filters for posting content over that social media platform?', 'What is your purpose of using AR filters' and 'What factors motivate you to use that social media app?' Some follow-up questions were posed to the participants based on their answers to the initial questions. However, they varied from participant to participant. We focused the interview on questions like 'How does the use of AR filters on the social media platform make you feel?' and 'What are the benefits/drawbacks of using AR filters on social media?' The interviews lasted from 30 minutes to 75 minutes.

3.3. Ensuring rigour

To ensure rigour in the methodology, we followed criteria specified by Chiovitti and Piran (2003), that is credibility, auditability and fittingness. First, for credibility, we ensured that the inquiry process was guided by the participants and used the participants' own words in the coding. We also confirmed that the theoretical constructs that emerged are as per the participant's meaning of the phenomenon. Second, for auditability, we have clearly mentioned the criteria used for sampling, data collection, interview process and data analysis. Furthermore, to ensure the quality and validity

of the data analysis, we discussed the conceptual model with three experts, two from the marketing area and one from the organisational behaviour area. First, we asked the experts to code the sub-sample (N=3) transcripts independently. All discrepancies were discussed between the coders till an agreement was reached. Second, the transcripts with the coding and interpretation were shared with the participants to confirm the credibility of the interpretation. Therefore, we made sure that the model is reliable and valid.

4. Findings

4.1. Coding process

We used a three-level coding process, that is open coding, axial coding and selective coding (Strauss and Corbin, 1994), and started the coding process from the first interview itself (Glaser and Strauss, 1967). During the open coding process, we followed line by line coding process. First, every fragment was tagged with a label describing its meaning. Next, using the constant comparison method, we categorised the codes into different categories at the axial coding stage. Table 2 represents the constructs, definitions and verbatim quotes. Finally, we condensed the relative categories into the core themes by examining their relationship during the selective coding process (see Table 3). We also referred to the relevant literature to check the relationship between the categories.

4.2. Use of AR filters on social media creates a higher 'ideal' standard for attractiveness and increases the ideal-actual gap

Since AR filters allow users to manipulate their appearance, social media users use AR filters extensively for their pictures or videos to project their most attractive selves. We found that, on average, our participants spent at least 2 hours daily on social media platforms, wherein most of the time, they used AR filters for content creation and posting. However, some of the participants (who perceived AR negatively) reduced their usage later on. Through the power of highly realistic superimposition and manipulation of appearance, AR filters allowed participants to project their improved looks/appearance on social media. This vast number of options extends their imagination and enhances their aspiration for how they would like to see themselves.

In addition, engaging with many others who are also using AR to enhance their images, the participants, consciously or unconsciously, start co-created artificial standards of attractiveness against which they judge themselves. This led to a perception of a new, redefined standard of what constitutes societal attractiveness. These artificial standards then redefine the representation of what one would like to be, as the bar goes up for every aspect of one's appearance.

Therefore, this results in an enhanced *ideal* self-concept (Higgins, 1987; Higgins et al., 1985). This is evident in the following quotes from our participants:

> *'Like for me, AR filters have created fake societal norms; people have made this perception that you have to look good in this. So basically, it has brought out the dark side of society as people don't usually like someone who is of dark complex (sic) or fat; I feel like people are over-exhausting themselves to look good through these filters'. (#R2, Female, 24)*

> *'Earlier, it was not there, but nowadays, everybody wants to look smart and beautiful with these filters and all. So people have forgotten their real identity and have started using these filters to look better than others'. (#R17, Female, 21)*

Table 2. Grounded theory analysis following Barta et al. (2022).

Construct	Definition	Example of participants' statement
Social comparison	The process of thinking about one or more other people in relation to the self (Wood, 1996)	*I am definitely conscious of how others perceive me on social media. I believe that most individuals are. That's why I always try to post my best pictures. (#R3, Male, 21)*
Ideal self-concept	Person's desired representation of their physical appearance that they aspire to (Higgins, 1987; Sirgy, 1982)	*These filters are so believable that you cannot distinguish between real and virtual makeup. So now I am more enthusiastic about yes, I can be more beautiful using AR makeup. (#R9, Female, 18)*
Actual self-concept	One's perception of how they really look (Higgins, 1987; Sirgy, 1982)	*It has happened to me that when I look at other people's photos, they look stunning because they use so many filters. But at the end of the day, it makes me think that I am not as good as them. (#R12, Female, 24)*
Inspiration	Mental stimulation to do something creative, bringing new ideas (Rauschnabel et al., 2019)	*I have used Sephora and other things, and they give you so many new ideas you cannot imagine. I mean, they offer you countless options in which you can be what you want to be. (#R8, Male, 19)*
Envy	The emotional state that occurs in response to a perceived or real threat to a social relationship (Buss et al., 1992)	*For sure, it is natural. I feel kind of missing out from the group as they all look much better than me. (#R10, Male, 22)*
Body (dis)satisfaction	Degree to which one is satisfied with one's present body attributes (Neumark-Sztainer et al., 2006)	*The AR filters make you think so much about your appearance. Unfortunately, they create so many drawbacks in your appearance, and you get dissatisfied with your body. (#R8, Male, 19)*
Self-confidence	Positive attitude towards oneself (Lenney, 1977)	*The way you are able to present yourself on Instagram using these filters gives me a lot of confidence. (#R6, Male, 35)*

AR: augmented reality.

Table 3. Coding process.

Open coding	Axial coding	Selective coding
Aspiration to become like others, comparison with others	Social comparison	
Change in perception of their own look, use of filters makes them more beautiful	Enhanced ideal self-concept	Ideal-actual gap
Not satisfied with their look	Reduced actual self-concept	
Inspired to achieve the desired look	Inspiration	Positive outcomes
Emotional jealousy desire to have perfect skin tone and body	Envy	Negative outcomes
Confidence about their appearance	Self-confidence	Well-being
Feeling of inferiority, dissatisfaction with the body	Body dissatisfaction	

Moreover, as the *ideal* standard for attractiveness gets redefined, respondents experience a wider gap between the ideal and the actual self-concept (Javornik et al., 2021; Lynch et al., 2009):

> *'Earlier, I was happy with my lips, but the day I used the lip filter, it changed my perception. I mean, it makes me look so beautiful that if somebody can make my lips like that, I am in' (#R7, Female, 24).*

Although Javornik et al. (2021) have discussed the concept of actual-ideal gap in the context of AR use, this research allows us to understand the process by which the gap bets broadened. The concept of enhanced 'ideal' standard of attractiveness that is co-created by the AR-generated content by social media users allows us to understand the process of broadening in detail.

4.3. Use of AR filters on social media platforms intensifies social comparison, leading to broadening ideal-actual gap

The participant interviews also revealed that while these filters create new attractiveness standards, people also compare themselves to others more. Earlier, users had limited power to manipulate their appearance. However, AR has empowered them to change skin tone, hair colour and makeup of their own choice. Therefore, when they post content using AR filters, the consumers of the content are more influenced by the enhanced appearance of others.

Social comparison (Festinger, 1954; Wood, 1996) is a natural tendency and has been evident since human evolution. Over the years, social media has been much more than a platform to connect and interact. Increasingly, social media has become a parallel world and a source of secondary/digital identity. Our respondents reported that they constantly compare digitally enhanced pictures of themselves with similarly enhanced pictures of others (Vogel et al., 2014). In other words, we found that the use of AR filters on social media intensifies the process of social comparison among users.

All participants in our research reported that they were highly conscious of the perception of others on social media networks; therefore, they tried their best to post their best pictures. Also, they wanted to increase their social influence through their post on social networks:

> *'Yes, of course, it has made me think of my look. I mean, these filter things have empowered all of us, and everybody is making themselves pretty. However, at the same time, personally, for me, I have started comparing myself to others. Moreover, I would say it is irresistible'. (#R13, Male, 20)*

Furthermore, we also found that as social comparison intensifies with the use of AR, it can influence an individual's self-concept both positively and negatively. For example, we observed that when participants compare themselves to people they perceive to be better-looking, it is detrimental to their actual self-concept or perception of what they really looked like:

> *'The Instagram filters make me feel that my body should be like her body. But in the end, the realisation is that I am not that beautiful as she is'. (#R12, Female, 24)*

Therefore, we found that the broadening of the ideal-actual gap happened in two ways: (1) through the redefinition of the 'ideal self' due to the ability of AR filters to provide highly realistic superimpositions and alteration in general appearances and (2) through diminished actual self-concept due to social comparison, triggered by the use of AR filters. While social comparison was detrimental to the actual self-concept of the participants, the augmentation power enhanced the ideal self-concept. Both processes resulted in increasing the gap between the ideal and actual self:

'For example, I took a raw picture and used filters, it will look totally amazing, and if I don't use filters, then it just will not be enhanced as such. So, you know, it will not give an appealing look'. (#R16, Male, 25)

'I used to post my pictures normally in my school or college days. I used to post them directly. However, after a year and one and a half years, I started realising that there were many things I should change in my profile as I saw that people were using filters and looking really smart and better. So, I realised that I should make my profile better. So that if a guy or girl may come across my profile can feel better, like your profile is good'. (#R4, Female, 27)

Researchers like Vogel et al. (2014) and Jiang and Ngien (2020) have found that the use of Facebook/Instagram is associated with higher social comparison. Our findings enrich this understanding by incorporating social comparison theory (Festinger, 1954) with the self-concept and the actual-ideal self-gap (Javornik et al., 2021), in exploring the effect of AR use on social media. Our findings allow a richer understanding of the process of broadening the ideal-actual gap.

4.4. Broadening of ideal-actual gap inspires users to try to reduce the gap by creative use of AR filters

Many participants reported that after they compared themselves with superior others on social media platforms and found that they were not as appealing as others, it inspired them to use AR filters to work on their appearance and reduce the ideal-actual gap. They also reported that they need to look better than others, so they use AR filters to achieve their desired look. As Lockwood and Kunda (1997) concluded in their study of how superstars influence self-view, an upwards comparison can benefit people who try to become more like their comparison targets:

'See, I am 27 now, but these filters make me feel like just 18. This is something which I never thought about. I mean, these effects inspire me to use filters to look pretty and young, and they are also easy to use'. (#R4, Female, 27)

In all, we found that when participants socially compare or self-evaluate themselves against others and experience a broader ideal-actual gap (particularly in the social dimension rather than private self-concept), they may opt to use AR filters creatively in order to bridge the gap. This reflects an attempt on their part to reduce the ideal-actual gap. Since inspiration is emotion-laden and typically has a positive valence (Rauschnabel et al., 2019; Silvia and Phillips, 2004; Thrash and Elliot, 2004), many users get inspired to use AR filters in order to enhance their actual self-concept, and to reduce the ideal-actual gap. Even when participants did not compare themselves with others on social media while using filters, they were inspired by the appearance enhancement offered by AR filters. In other words, with or without social comparison, participants reported that they use AR filters in an attempt to enhance the actual self and reduce the ideal-actual gap:

'Whatever you find that is not good in you, then you use the filter, and that thing is better now; for example, if somebody does not like the nose, or like if somebody has a broad nose and then do that filter, that makes the nose slimmer. I think whatever is missing in you is basically fulfilled by the filters. So, I feel satisfied as the picture looks perfect now'. (#R11, Female, 23)

'Yeah. So, I always wanted to see myself in specs, like, how would I look? So, there was a filter once in a while. So that was something that I really liked. Like, you know, personally, that inspired me to have zero number specs just for the fashion purpose'. (#R6, Male, 35)

Interestingly, participants reported that they sometimes take hours to make a picture that could be posted on the platforms. They were always attracted to unique and new looks and appearances. So, they also wanted to post something unique that caught the attention of others. It resulted in a creative process to achieve their desired look and helped to enhance the actual self-concept of an individual.

We found that participants used creativity in the social media context to achieve their desired look. The participants considered creativity to be an important personal characteristic in narrowing the ideal-actual gap. They also narrated that they have become more creative, as they are continuously trying to achieve their ideal self in unique and vivid ways:

> *'If you are using social media to introduce yourself, you have to add something, some new ideas or some creative stuff, that people will automatically like to focus over it, and they will give you a reply with that'. (#R16, Male, 25)*

> *'These AR filters allows to experiment with my look in many more ways. I can be who I want to be, so now I do not feel like I am not that good looking as others'. (#R18, Male, 23)*

In their experimental research on customer engagement, Jessen et al. (2020) found that AR-enabled applications heighten customer creativity by offering a variety of playful, fun experiences that users can have fun experimenting with, and such 'creative customer engagement' (Jessen et al., 2020: 89) can lead to higher satisfaction. Since digital natives are creative users of such digital technologies (Ameen et al., 2020; Srivastava et al., 2023), it should be expected that younger users of AR filters on social media would also increasingly use their own creativity to use or even create AR filters in an attempt to reduce the ideal-actual gap. This is borne out by our respondent interviews, as illustrated above.

4.5. The dark side of broadening ideal-actual gap

When participants reacted negatively to the enhanced ideal-actual gap, they experienced a feeling of envy. For instance, some participants narrated that when they saw others with perfect bodies and thought that they did not have that kind of body, it resulted in anxiety and envy:

> *'For me personally, I feel that there is emotional jealousy among people. Nowadays, everybody wants to get a perfect skin tone and a perfect body, but unfortunately, they do not have that'. (#R12, Female, 24)*

Similar observations have been found in the previous literature. For instance, Vogel et al. (2014); Jiang and Ngien (2020); Meier and Schäfer (2018) have explored the negative effects of social media use in terms of envy and social comparison.

4.6. Ideal-actual gap and feelings of well-being

We found that the ideal-actual gap affects the well-being of an individual in both positive and negative ways. On the positive side, it inspires users to try to reduce the gap between the ideal self-concept (artificial standard of attractiveness generated by active use of AR filters by social media users) and the actual self-concept on physical attractiveness. When users achieve this, it enhances their self-confidence and their body satisfaction. The following comment illustrates this:

> *'I use these filters for me. What I feel is that my skin is oily, and I have pimples. So, while using that AR filter, I really found that I am looking so beautiful, my skin is so clean, and sometimes it gives so much confidence to you that yeah! okay, I can get this much beauty, and I can change myself'. (#R1, Female, 22)*

Feelings of inspiration have been found to generate several positive outcomes. For example, Hinsch et al. (2020) showed that AR marketing provokes psychological inspiration, resulting in behavioural inspiration. Rauschnabel et al. (2019) concluded that benefits generated through AR inspire users, forming a positive attitude towards the brand. Our participant reports confirm this.

On the other hand, some users reported that the heightened ideal-actual gap triggered a feeling of envy among them, leading to lower self-confidence and body dissatisfaction:

> *'I mean the impact was such that I started envy people, and completely loose my confidence' (#9,Female, 18)*

As mentioned in earlier sections, researchers have more often focused on the negative effects of social media use and social comparison (Siddegowda et al., 2023). For instance, Skogen et al. (2021) found that social media self-presentation significantly influences mental health and quality of life across genders. Similarly, Fan et al. (2020) found that others' self-presentation diminishes users' subjective well-being, and upwards social comparison led to feelings of relative deprivation. However, we found that many of our participants reported positive responses in terms of getting inspired to use their own creativity to reduce the ideal-actual gap, and thereby improve their sense of body satisfaction and self-confidence. We have discussed this further in the Section Discussion.

Second, our analysis also showed that when participants regained body satisfaction and self-confidence, it motivated them to use the app continuously:

> *'I think I use Snapchat just for the filter thing. I give myself the look that I want, so I do not visit other media platforms. So even for posting photos on Facebook or Instagram, I use Snapchat filters and then share them with other platforms'. (#R13, Male, 20)*

Thus, the intention to continue usage of a social media platform could be an outcome of positive feelings associated with narrowing the actual-ideal gap on physical attractiveness.

5. Discussion

Over the last decade, social media platforms have become increasingly relevant, especially in the lives of digital natives. The current study attempted to explore how the use of AR filters by social media users can affect the self-concept of users. Through a grounded theory approach, we attempt to unpack both positive and negative effects. The analysis offers several interesting and novel insights, which we will discuss in relationship with existing theory and research in this section.

First, the current study develops a fine-grained understanding of the psychological processes involved in forming the ideal-actual gap (Javornik et al., 2021, 2022), through an analysis of narratives of actual users. We found that by using AR's ability to manipulate one's appearance and its increasing use over social media platforms, users have themselves co-created artificial standards for attractiveness. One of the most interesting findings from the analysis was that this artificial standard of attractiveness then replaces users' definition of an 'ideal' self-concept. Thereby, we extend Javornik et al.'s (2021) work by a richer analysis of how the concept of enhanced 'ideal' standards of attractiveness leads to broadening the gap between ideal and actual attractiveness.

Second, we add to the body of research on social comparison and social media, by incorporating social comparison theory with self-concept and the ideal-actual gap (Javornik et al., 2021). Specifically, we found that the increasing use of AR filters on social media and the rising consumption of such content by users is triggering more social comparison among them. Earlier researchers

have found that using Facebook/Instagram is associated with higher social comparison and is further related to outcomes like self-esteem and social anxiety (Jiang and Ngien, 2020; Reer et al., 2019; Vogel et al., 2014). Our analysis suggests that the process of social comparison, combined with the capabilities of AR of highly realistic superimposition, exacerbates the experienced gap between ideal and actual self-concept in two ways, both by enhancing the 'ideal' standard of attractiveness and by reducing the 'actual' attractiveness of self through social comparison.

Third, analysing the effects of this broadening gap, we found that the gap between the ideal and actual self could be experienced either positively or negatively, as suggested by researchers like Gerber et al. (2018). However, our findings suggest that positive responses could be more common in the case of users of AR filters as compared to more passive forms of social media. We explain this in detail below.

The negative effects of social media use and social comparison on social media have been explored by several researchers (Jiang and Ngien, 2020; Meier and Schäfer, 2018; Vogel et al., 2014). Our methodology allowed us to explore the negative pathways associated with such social comparison through the lens of self-concept. For example, some of our respondents reported adverse reactions like anxiety and envy due to the broadened ideal-actual gap, and constant comparison with other users of filters. These findings are consistent with Higgins' (1987) self-discrepancy theory, which concludes that a high level of discrepancy between the self-concept and the ideal self-guide was associated with dejection-related emotions like disappointment and dissatisfaction.

On the positive side, however, our findings indicated that many participants were inspired to use the available filters creatively, in order to narrow the ideal-actual gap. As mentioned earlier, any discrepancy between the actual and ideal self-concept would be expected to motivate individuals to attempt to restore a match between the two (Higgins, 1987). Further, self-enhancement theories suggest that behaviour of individuals will be directed towards restoring one's self-worth (Swann et al., 1987). Our findings illustrate what these theories suggest in the domain of the use of AR filters on social media.

As mentioned in earlier sections, researchers have more often focused on the negative effects of social media use and social comparison (Siddegowda et al., 2023). For instance, Skogen et al. (2021) found that social media self-presentation significantly influences mental health and quality of life across genders. Similarly, Fan et al. (2020) found that others' self-presentation diminishes users' subjective well-being, and upwards social comparison led to feelings of relative deprivation. However, we found that many of our participants reported positive responses in terms of getting inspired to use their own creativity to restore their ideal-actual gap and, thereby, feeling a sense of body satisfaction and self-confidence.

We offer two possible explanations for the divergent responses, one based on the unique characteristics of AR as a technology and the other rooted in psychological differences between individuals.

First, the prevalence of positive responses among our participants may be attributable to the fact that AR tools offer an active solution to the problems of social anxiety and self-esteem that social comparison may have led to otherwise. For example, Meier and Schäfer (2018) found that social comparison can lead to inspiration when it acts through benign (rather than malicious) envy. Our findings suggest that these positive effects of social comparison may be more benign in the AR context, as AR tools offer a positive way to deal with the ideal-actual gap. Conversely, negative responses may be associated with more passive technologies that do not offer such agency to users.

The presence of both positive and negative responses reported by our participants can also be explained by the body of research on approach/avoidance orientations to stress (Roth and Cohen, 1986) that focus on personality and motivation-related differences between individuals on a tendency to move towards positive stimuli (approach) or away from negative stimuli (avoidance). For example, Elliott and Thrash (2002) find that approach temperaments can be directed towards

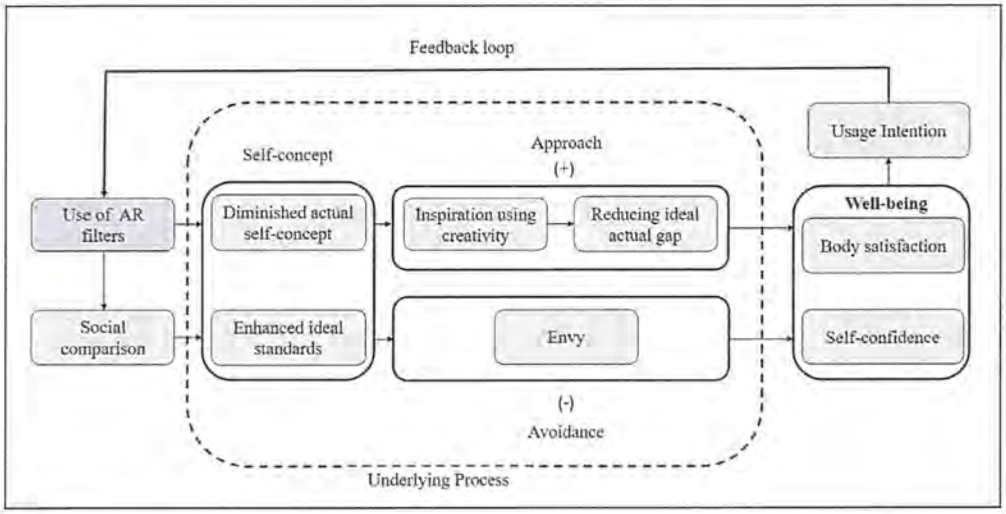

Figure 1. Conceptual model.

self-enhancement, while avoidance temperaments can be directed towards self-protection. This framework (Figure 1) may be used to build explanations and test hypotheses to determine why certain individuals experience and react to the ideal-actual gap in a positive way while others experience and react to it negatively. This may provide insight into the divergent responses of individuals towards the phenomenon of the ideal-actual discrepancy.

Fourth, we further explored how participants felt as a result of these positive and negative responses. Participants narrated that restoring ideal-actual gap using AR caused them to experience body satisfaction and self-confidence, and motivated them to use the app continuously. On the other hand, participants who reacted to the ideal-actual gap negatively felt dissatisfied with their bodies and feelings of low self-confidence, which resulted in the intention to discontinue the app usage. Since our research focuses on one aspect of self, that is physical appearance, we consciously choose to use the term 'self-confidence' rather than self-esteem, which is a more global concept, that can be generalised to multiple aspects of self. Two specific aspects of well-being that may be more relevant to the AR/social media context also emerged from our research, namely, self-confidence and body satisfaction.

Overall, we found that the gap between ideal and actual self-concept can affect the well-being of an individual in both positive and negative ways. On the positive side, it inspires users to attempt to narrow the gap between the ideal and actual self. Moreover, when the users achieve this, it enhances their self-confidence and body satisfaction, and strengthens their usage intention and engagement. On the other hand, on the negative side, it may lead to dissatisfaction and disengagement with the platform. By doing so, we extend the work of Javornik et al. (2022) by creating a complete explanation of the effect that using AR filters on social media has on self-concept, well-being and continued use.

6. Implications, limitations and future research

6.1. Theoretical implications

The study contributes to the existing body of knowledge in the following ways: First, it is one of the few studies that explore the effect of using AR filters on self-concept in the context of social

media. As discussed earlier, although some prior research (e.g. Javornik et al., 2021) has examined the impact of AR use on self-concept, their focus is on retail consumers rather than social media users. Our research focuses on the effect of continued AR filter use on social media users. In addition, researchers like Javornik et al. (2022) and Ibáñez-Sánchez et al. (2022) who have studied the use of AR filters by social media user, have primarily focused on understanding why AR filters are used, using uses and gratification theory. The focus of this research, however, is not on understanding the motivation for use but rather its effects and felt experiences.

The inductive qualitative methodology used in this research left open the possibility of discovering (rather than testing) new concepts and relationships, which is extremely valuable when theory is under-developed. Extant literature has mostly used deductive logic to derive and test hypotheses involving the impact of various motivations for using AR filters on satisfaction, e-wom (Ibáñez-Sánchez et al., 2022); product choice confidence (Javornik et al., 2021), and use frequency (Javornik et al., 2022), but they do not offer insights into how the broadening of ideal-actual gap is experienced, and its effect on self-concept, well-being and usage intention. Our analysis of participant narratives allowed us to identify inspiration, creativity, body satisfaction, self-confidence and envy as intervening factors between the use of AR filters and the self-concept. Therefore, we offer a more fine-grained understanding of the experience of social media users, by using concepts from psychology and social psychology. Future research can test and refine these findings.

Second, following the research agenda of Kumar (2021), we offer exciting insights into the bright and dark sides of using AR filters on social media. For example, while inspiration has been found to be an important factor for behavioural intentions in virtual try-on retail (Rauschnabel et al., 2019), we identified inspiration as a positive emotional response to narrow the gap between ideal attractiveness and actual attractiveness. In addition, user creativity was a significant personal trait that helped reduce this gap. Future research can explore the positive effects further, both related to the nature of AR technology, and to the personality of users, as explained in the Discussion section. At the same time, our research also illustrated the adverse effects of AR use in terms of respondents experiencing envy. Future researchers may want to examine the conditions under which AR users experience positive and negative consequences on social media using the approach/avoidance framework, as suggested earlier. Factors that could influence the positive or negative pathways include an individual's level of self-esteem or positive body image, cultural norms, technological factors (such as the quality and novelty of the technology) and personality traits such as openness to experience or approach orientation. Investigating these factors can help identify ways to mitigate negative effects on well-being and intention to use the technology. For example, researchers could examine whether users with positive body images react positively to a larger ideal-actual gap while users with lower body images react negatively. They could also investigate whether encouraging users to use AR filters to restore their ideal self-image could lead to negative outcomes like increased social media addiction under certain conditions.

Next, our research also highlighted the influence of AR on well-being and continued intention to use the social media platform through the lens of self-concept. Existing research concludes that AR filters influence the psychological well-being of the users, wherein self-acceptance and positive affect represent well-being (Javornik et al., 2022); the current study adds two new dimensions to the psychological well-being (i.e. self-confidence and body satisfaction) that the usage of AR filters can trigger. We propose that while factors like utilitarian, hedonic and social values are important for usage intentions (Hsu et al., 2021; Rauschnabel et al., 2017) in the AR marketing context, the role of self-concept may be more prominent than other factors for the usage intention in the social media context. Fourth, we propose that the use of AR widens the idea-actual self-gap, not only through AR's power of superimposition (Javornik et al., 2021) but also through the social comparison that is triggered by the use of AR filters over social media. This may help future

High			
Social Comparison	Reduce actual self-concept	Reduce actual self-concept Enhance ideal self-concept	
	No change in ideal-actual gap	Enhance ideal self-concept	
Low			High
	AR's power of highly realistic superimposition and manipulation		

Figure 2. Ideal-actual gap and augmented reality.

researchers to build a more nuanced understanding of self-concept and body image in the case of users of AR filters on social media.

Finally, based on our participants' narratives and our analysis, we propose the following ideal-actual gap matrix (Figure 2). We propose that the broadening of the ideal-actual gap can result from the AR power of highly realistic superimposition through intensifying social comparison, or through a combination of both. While AR's power of highly realistic superimposition is expected to enhance the ideal self-concept, in contrast, social comparison is expected to reduce the actual self-concept. In this study, we provide the initial food for thought for future researchers to explore further these dimensions and the psychological mechanism underlying such processes.

6.2. Practical implications

The study offers vital practical implications for marketers, social media and brands using these platforms for their promotion and engagement-related activities. First, social media apps have become the prime platform for many promotional campaigns. Many brands like NYX, Gucci and OnePlus have introduced their AR ads, which are gaining great attention among users. For example, 'Diwali Festival of light' by OnePlus, NYX professional makeup and Gucci debut are some campaigns that receive massive attention from people. We demonstrate how these AR filters can influence self-concept, body image and behavioural intentions. Therefore, companies/brands in the race to start AR ad campaigns can get a clearer picture of how AR can affect user experience and behaviour through the self-concept lens.

Most importantly, our findings also highlight that ideal self-achievement and reduced ideal-actual gap can positively influence self-confidence, body satisfaction and behavioural intentions. However, it can also lead to adverse outcomes like low body image and feelings of anxiety. Therefore, marketers are encouraged to provide a more realistic AR ad experience to maintain higher standards of marketing ethics and responsibility towards consumer health. The negative effects are concerning since there were a significant number of cosmetic procedures conducted, including popular procedures such as lip injections, nose reshaping and eyelid surgery (Hermans, 2022). These negative responses to the ideal-actual gap may contribute to the demand for such procedures, and this warrants attention from policymakers, marketers and researchers. Future research could explore strategies to mitigate these potentially harmful effects.

Moreover, social media platforms now allow users to create their own filters; we found that this creativity helps them achieve their ideal self-concept and narrow the ideal-actual gap. Therefore, companies looking to inspire/engage users with the brand can incorporate features that involve more user creativity.

6.3. Limitations

This study has some limitations that should be noted. First, the grounded theory approach was utilised, and other inductive or deductive approaches could be employed to verify the findings. Second, the sample was restricted to participants from India, so the Generalisability of the findings to other countries may be limited. In addition, the use of a student sample may constrain the external validity of the study. Finally, the study relied on self-reported data. Thus, future research may benefit from incorporating observational and longitudinal techniques to verify the findings.

7. Conclusion

AR has revolutionised the way people interact, create and share content on social media. Scholars have highlighted AR's potential to replace existing realities and disrupt traditional communication methods (Kumar et al., 2023a; Rauschnabel et al., 2022a, 2022b). As a result, it is crucial to examine the ethical and societal implications of AR. The ethical boundaries surrounding these technologies should be defined to ensure their responsible and positive use. Instagram's removal of plastic surgery filters due to their detrimental impact on mental health further emphasises the need for caution. Studies (Chen et al., 2019) have confirmed an increase in cosmetic procedures following the introduction of AR filters on social media platforms. As AR is primarily utilised in social media, researchers must prioritise enhancing user well-being through responsible AR use.

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3

Assessment of Eating Disorders: Interview Versus Questionnaire

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(Accepted 13 March 1995)

Objective: *This study assessed the validity of the Eating Disorder Examination—Questionnaire (EDE-Q) in identifying eating disorder symptoms in female substance abusers.* **Method:** *Subjects were assessed for the presence of eating disorder behaviors and attitudes using the Eating Disorder Examination (EDE), a semistructured interview, and the EDE-Q. The results of the two measures were then compared.* **Results:** *Results showed that the EDE-Q does idenfity eating disorders in this population. It is more accurate in assessing purging than the more complex features of binge eating and dietary restraint.* **Discussion:** *Eating disorders and substance abuse co-occur at a higher rate than expected by chance, and recent findings indicate that eating disorders often go undetected among patients with substance abuse. The EDE-Q appears to be an effective screening instrument for detecting the presence of eating disorder symptoms in this population. © 1996 by John Wiley & Sons, Inc.*

The Eating Disorder Examination (EDE) is an interviewer-based, semistructured interview that was developed to assess the specific psychopathology of eating disorders (Fairburn & Cooper, 1993). It is currently viewed as the "gold standard" in the assessment of eating disorders (Wilson, 1993a). Numerous studies have demonstrated the reliability and validity of the EDE (Beglin, 1990; Fairburn & Cooper, 1993; Rosen, Vara, Wendt, & Leitenberg, 1990). Nevertheless, there are disadvantages associated with its use, and in many instances the EDE is not a viable option. In such cases a self-report questionnaire may be the only feasible alternative.

Self-report questionnaires offer a number of advantages over interviews. Administration of a questionnaire is usually simple, and most can be scored by nonprofessional staff. This is in contrast to an investigator-based interview which often requires intensive training. Self-report questionnaires are economical and often require less time than an interview which is also an advantage for both assessors and subjects.

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On the negative side, many concepts are difficult to assess accurately with a self-report questionnaire. In the case of eating disorders, where certain concepts such as binge eating refer not only to precise clinical definitions, but also to common, vague everyday notions of excess (Fairburn & Wilson, 1993), this issue seems especially salient. Specifically, in assessing the frequency of binge eating a self-report questionnaire leaves the decision of what constitutes a large amount of food to the subject. Beglin and Fairburn (1992) have demonstrated that when young women refer to a binge, they are responding primarily to a sense of loss of control, not the amount of food consumed. Thus, a subject who reports consuming large amounts of food in a "binge" may simply be rating the degree to which she felt out of control. This issue is not as problematic when an investigator-based interview is used as the interviewer decides whether an episode of eating meets the appropriate requirements.

Fairburn and Beglin (Beglin, 1990; Fairburn & Beglin, 1994) completed an assessment of a self-report questionnaire version of the EDE (EDE-Q) with both a community and a clinical eating disorders sample. The goal of this study was to determine which of the specific features of eating disorders could and could not be assessed by a self-report questionnaire. In this study, the EDE-Q was compared directly with the EDE. The general findings indicated that the EDE-Q was able to assess accurately those behaviors that are relatively unambiguous in nature. Not surprisingly, the EDE-Q did not perform as well with items that were more conceptually complex. The diagnostic capabilities of the EDE-Q appeared to be dependent on the population it was used to evaluate. Overall, the EDE-Q did not perform as well with the community sample as it did with the clinical eating disorders sample. The primary aim of the present study was to replicate the Fairburn and Beglin study with a different clinical population.

Although assessing the level of EDE-Q performance with a clinical sample not currently diagnosed with eating disorders is important in general terms, determining whether or not the EDE-Q performs acceptably with a substance abuse population has additional significance. Eating disorders and substance abuse co-occur at a rate greater than that predicted by chance (Wilson, 1993b), with approximately 25% of women receiving treatment for alcohol abuse also meeting criteria for an eating disorder (Peveler & Fairburn, 1990). In addition, recent findings indicate that in many cases eating disorders go undetected in patients being treated for substance abuse (Striegel-Moore, Cronan, Goebel, Pena, & Scheibe, 1992; Taylor, Peveler, Hibbert, & Fairburn, 1993). Were the EDE-Q to satisfactorily detect cases in a substance abuse population, it could be used as an efficient means to routinely screen for eating disorders in this high-risk sample.

METHOD

Design

All subjects were assessed for the presence of eating disorder behaviors and attitudes using the EDE-Q and the EDE. At the end of the interview, weight and height measurements for each subject were obtained. Both the questionnaire and the interview were given at the same appointment and evaluated the same 28 days prior to assessment. The EDE-Q was administered prior to the interview.

Subjects

The subjects in this study comprised a diverse group of women seeking help for substance abuse or dependence. The 48 subjects were recruited from five locations—one

outpatient and three inpatient drug/alcohol treatment centers, and one outpatient eating disorders clinic. Both outpatient clinics served a university population. Two of the inpatient units served, in general, middle-class patients while the other inpatient unit operated primarily as a short-term detoxification center in a small urban community. All women who were approached in the detoxification center and all but 3 women from the other inpatient units agreed to participate in the study; 39 of the 48 subjects were recruited from these two locations. The outpatient sites were marked by a lower rate of participation and provided the remaining 9 subjects.

Measures

The 12th edition of the EDE (Fairburn & Cooper, 1993) was used as the interview measure for this study. The EDE is designed to assess the specific psychopathology of eating disorders and also generates eating disorder diagnoses according to criteria of the 4th ed. of the *Diagnostic and statistical manual of mental disorders* (DSM-IV, American Psychiatric Association, 1994). Although the EDE can be used to assess a 3-month period in order to meet DSM-IV diagnostic criteria, the interview focuses on the previous 28-day period. This latter form of the interview was used in this study to facilitate comparison with the self-report measure which only assesses a 28-day period.

The EDE-Q (Fairburn & Beglin, 1994) is a 38-item self-report questionnaire, with each item being drawn from a corresponding question on the EDE. In most cases, the wording of the EDE-Q is taken directly from the main probe question of the EDE. Both the EDE and the EDE-Q use the same 7-point, forced choice, coding scale. The higher the number on the scale the greater the severity or presence of a feature.

Data Analyses

The EDE and EDE-Q assess the main features of eating disorders in two ways: First, by assessing the frequency of key behavioral features of eating disorders such as binge eating and purging; and second, through subscales that generate dimensional measures of disturbance. Analyses evaluated the EDE-Q's accuracy on both types of measurement as well as assessed diagnostic validity.

All EDE-Q items and their EDE counterparts were correlated to determine the degree of similarity in the ratings obtained by each measure. The same items were then tested for significant differences. Normally distributed data were analyzed with parametric tests (Pearson's r and Students's paired t tests), while nonparametric tests (Kendall's tau-b and Wilcoxon's matched pairs signed rank sum test) were used with nonnormally distributed data. McNemar tests were used to analyze differences between EDE and EDE-Q diagnoses. Finally, regression analysis was used to determine the effect of such factors as length of sobriety and alcohol versus drug usage.

RESULTS

Subjects

The sample consisted of 48 women with ages ranging from 18 to 56 years ($M = 32.6$). All subjects were either currently in treatment for their substance abuse or attending Alcoholics Anonymous (AA). Eighteen women were in treatment for alcohol abuse alone

Table 1. Comparison of the Eating Disorder Examination (EDE) and the Eating Disorder Examination-Questionnaire (EDE-Q) assessment of key behavioral features

	M (*SD*) of Differences Between the EDE-Q and EDE	Kendall's tau-b	Wilcoxon Matched Pairs z score
Self-induced vomiting	−0.06 (0.6)	1.00*	0.01 (NS)
Laxative misuse	−0.47 (3.4)	0.99*	0.01 (NS)
Objective bulimic episodes	2.14 (15.0)	0.53*	−0.61 (NS)
Dietary rules	0.39 (2.5)	0.49*	−0.87 (NS)

* $p < .0001$, NS = not significant.

and 6 women for drug abuse without alcohol. The remaining 24 women abused both alcohol and drugs.

Assessment of Key Behavioral Features

The four key behavioral features of eating disorders—self-induced vomiting, laxative abuse, uncontrolled overeating (objective bulimic episodes), and strict dieting (dietary rules)—were assessed to determine the level of agreement between the interview and self-report measure. Table 1 shows the mean of the differences between the self-report measure and interview (EDE-Q rating minus EDE rating), Kendall's tau-b correlation coefficient, and Wilicoxon matched pair z scores.

The EDE and EDE-Q were significantly correlated on all four measures. Self-induced vomiting and laxative misuse were the two most strongly correlated items and neither exhibited a significant difference between the two measures. Some caution must be used in interpreting these results, however, especially those relating to laxative misuse, since both items were frequently rate as 0. Only 2 subjects rated laxative use above 0. While self-induced vomiting was a more common behavior among the subjects, the number of subjects reporting this behavior is again low.

Objective bulimic episodes and dietary rules were not as highly correlated as self-induced vomiting, although agreement was significant. Although the discrepancy between the self-report questionnaire and interview was not significant for either item, both objective bulimic episodes and dietary rules showed a higher mean difference and a lower correlation than self-induced vomiting. The lack of significance in the Wilcoxon z scores may be attributable to the small sample size in this study.

Assessment of Restraint, Weight, and Shape Subscales

Four subscales can be obtained from both the EDE and the EDE-Q, with the three key ones being dietary restraint, weight, and shape concern (Fairburn & Beglin, 1994). The EDE and EDE-Q scores were significantly correlated for each of the three subscales (Table 2).

Table 2. Comparison of the Eating Disorder Examination (EDE) and the Eating Disorder Examination-Questionnaire (EDE-Q) subscales

	M (*SD*) of Differences Between the EDE-Q- and EDE	Pearson's *r*	*t*	Percentage Agreement Within 1.0
Dietary restraint	0.33 (1.2)	0.75*	1.88(NS)	75.0
Weight concern	0.35 (0.9)	0.85*	2.72**	81.3
Shape concern	0.63 (1.0)	0.84*	4.28*	66.7

* $p < .0001$, ** $p < .01$; NS = not significant.

Although dietary restraint was the only subscale that did not exhibit a significant difference between the two measures, weight concern showed the greatest level of agreement. All three subscales were overestimated by the EDE-Q. Shape concern showed the greatest difference and lowest percentage of agreement between EDE-Q and EDE ratings, and was thus the most inaccurately assessed EDE-Q subscale.

Assessment of Bulimia Nervosa and Eating Disorders—Not Otherwise Specified (EDNOS)

Each subject's EDE and EDE-Q scores were assessed to determine if they met DSM-IV diagnostic criteria for bulimia nervosa, anorexia nervosa, binge eating disorder (BED; EDE operational criteria, Fairburn & Cooper, 1993), or EDNOS. While no EDE operational criteria have been established for the diagnosis of EDNOS, this diagnosis was used for cases that met all but one of the diagnostic criteria for another eating disorder. Thus, all EDNOS diagnoses in this sample were subthreshold cases of another eating disorder.

The degree of agreement between the EDE and EDE-Q was calculated for each diagnosis. The EDE and EDE-Q agreed on 42 noncases and 3 cases of bulimia nervosa. The EDE-Q failed to diagnose three cases of bulimia nervosa assessed by the EDE. This difference was not significant (McNemar test probability = .25). These three cases were, however, rated as subthreshold bulimia nervosa by the EDE-Q and account for three of the five EDE-Q EDNOS cases; the final two EDNOS cases were also rated as subthreshold bulimia nervosa. The EDE agreed on one of these cases and disagreed on the other case. If the subthreshold cases are combined with the bulimia nervosa cases, then the only disagreement between self-report and interview lies in one noncase that the EDE-Q inaccurately assessed as subthreshold bulimia nervosa. Thus, when strict operational criteria were applied the EDE-Q underassessed the rate of bulimia nervosa in this sample, and overdiagnosed when the criteria were slightly relaxed.

Assessment of Anorexia Nervosa

It was not possible to assess the level of agreement between the EDE and EDE-Q for the diagnosis of anorexia nervosa, since only one case was diagnosed by the EDE-Q and no cases were diagnosed by the EDE. Descriptively, however, the differences between subscale scores of the EDE-Q and EDE for this case were substantially larger than the means for this sample.

Other Factors Related to EDE/EDE-Q Agreement

Total discrepancy scores were calculated for each subject by adding the difference between the EDE and EDE-Q scores on all corresponding items together. This provided a rating that indicated the level of agreement between the EDE an EDE-Q for each subject. Total discrepancy scores ranged from 0 to 69 with a mean of 11 (SD = 21.7).

Five variables, namely age, alcohol usage (yes or no), drug usage (yes or no), length of sobriety, and recruitment location were assessed to determine their influence on the total discrepancy score. None of these variables accounted for a significant proportion of the total discrepancy score variance.

The final subscale score that can be calculated from the EDE and EDE-Q is a total subscale score which provides a general continuous measure of eating disorder psycopathology. The larger the ratings on individual items throughout both tests, the higher the

total subscale score. Both the EDE and the EDE-Q total subscale scores were assessed to determine their influence on the total discrepancy score. Although the total subscale scores for the two measures were highly correlated ($p < .0001$), only the total discrepancy score. While the EDE total subscale score showed no significant effect ($p < .76$), the EDE-Q total subscale score accounted for 22% of the total discrepancy score variance ($p < .01$), indicating that as EDE-Q scores increase so does the discrepancy with the EDE.

DISCUSSION

This study sought to determine which of the specific features of eating disorders could be accurately assessed by self-report in a clinical sample of substance abusers. Methodology and data analyses closely followed those of Fairburn and Beglin (1994).

It is important to note that several problems exist in generalizing the Fairburn and Beglin (1994) study to substance-abusing populations, which reinforces the necessity for evaluating the EDE-Q specifically with this population. Since both drugs and alcohol have reported effects on appetite and weight, the chances for external factors to influence the EDE-Q scores may be higher in this group than with other clinical populations. Any measure that is used to assess eating disorders in substance-abusing samples must be capable of separating weight and appetite changes that are a pure side effect of the substance abuse and those that are indicative of a concurrent eating disorder. In some severe casses, this distinction may not be possible to make until the drug abuse has been reduced.

Results were first analyzed in terms of the key behavioral features of eating disorders, namely self-induced vomiting, laxative misuse, objective bulimic episodes, and dietary rules. The self-report asseessment of laxative misuse could not accurately be evaluated since only 2 subjects reported this behavior. The general trends noted by Fairburn and Beglin (1994) were confirmed by this study. Whiel self-induced vomiting appeared to be effectively assessed by the EDE-Q, correlation coefficients were considerably lower for the more ambiguous behaviors, objective bulimic episodes, and dietary rules. While none of the differences between the EDE and EDE-Q scores reached significant levels, this may be due in large part to the small sample size. In general, comparison of correlation coefficients indicates that the EDE-Q performance with the substance-abusing sample fell somewhere between its performance with the community sample and the patient sample reported by Fairburn and Beglin (1994).

Shape and weight concern subscale scores showed the same trends as discussed by Fairburn and Beglin (1994). Both subscales showed a significant difference between the EDE and EDE-Q ratings, although they were highly correlated. The shape concern subscale displayed the highest degree of difference, and as noted by Fairburn and Beglin (1994), this is probably related to the large number of complex items assessed by this subscale.

Overall, dietary restraint results were almost identical to those reported by Fairburn and Beglin (1994) with their patient sample. Despite this, certain items within this subscale may be problematic for substance-abusing samples. Although the behaviors and attitudes measured by dietary restraint are less ambiguous in nature than those for weight and shape concern, several of the specific items included in dietary restraint may be more difficult for a substance-abusing population to answer. Specifically, two questions, one concerning avoidance of eating for a period of 8 or more waking hours and the other concerning a desire for an empty stomach, showed a tendency to be misconstrued; these items also showed the greatest mean of differences and the largest z scores of the items

composing dietary restraint. Many subjects reported during the interview that they did avoid eating for long periods of time and often desired a truly empty stomach. The reasons for these behaviors, however, were often not weight and shape related but connected with a desire to avoid vomiting as the result of drinking binges. One subject also expressed a desire to "leave as much room for alcohol [as possible] in my stomach." Empty stomach shows the greatest chance for producing a misleading rating since it does not specify that the reason for wanting an empty stomach should be related to shape and weight.

Statistically the EDE-Q performed well when diagnosing bulimia nervosa. That the EDE-Q missed three cases of bulimia nervosa is also somewhat mitigated by the fact that it assessed these cases as subthreshold bulimia nervosa. What these cases may indicate is a need for additional evaluation in borderline bulimia nervosa cases. Although the effectiveness of the EDE-Q in diagnosing anorexia nervosa cannot be statistically calculated, the one EDE-Q diagnosed case of anorexia nervosa highlights some necessity for caution in using the EDE-Q for this purpose in this population. Comparison of subscale difference scores for this case implies that this case was significantly misassessed by the EDE-Q.

The elevated scores for the anorexia nervosa case also underline one other significant trend with this population. Although age, drug and alcohol use, length of sobriety, and location of recruitment did not account for a significant percentage of the variance of the total discrepancy scores (which reveal the amount of overall EDE/EDE-Q disagreement for each subject), the EDE-Q total subscale score did. This indicates that the EDE-Q assessed quite accurately subjects who exhibited very low levels of eating disorder behaviors and attitudes; these subjects are, in general, the easiest to assess by interview as well. As EDE-Q score increased so did differences with the EDE. Assuming that the EDE provides an accurate baseline, this indicates that the EDE-Q became less reliable as eating disorder behaviors and attitudes became more frequent.

While this trend is not surprising, what it may point to is a need for additional assessment in cases where EDE-Q scores are elevated. Both drug and alcohol abuse can interact with several features evaluated in the process of assessing eating disorders, namely weight, appetite, and dietary restraint. Following up elevated EDE-Q scores with interviews would allow these factors to be teased apart where possible, and to be rated as unamenable to assessment when not. Such follow-up would also address the bulimia nervosa diagnostic issues. Even with such follow-up, however, use of the EDE-Q in both research and clinical settings would still allow for a large majority of substance-abusing women to be accurately screened without necessitating an interview for every subject or patient.

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BRIEF REPORT

Reducing Social Media Use Improves Appearance and Weight Esteem in Youth With Emotional Distress

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Adolescence and young adulthood are vulnerable periods in which mental health challenges often emerge. Cross-sectional research has shown that high social media use (SMU) is associated with poor body image in youth, a known predictor of eating disorders; however, high-quality experimental evidence is scarce, limiting the ability to make causal inferences. The present study experimentally examined the effects of *reducing* smartphone SMU on appearances and weight esteem in youth with emotional distress. A randomized controlled trial was conducted where 220 participants (17–25 years; 76% female, 23% male, and 1% other) were assigned to either an intervention (SMU limited to 1 hr/day) or control (unrestricted access to SMU) group. SMU was monitored via screen time trackers and submitted daily during 1-week baseline and 3-week intervention periods. Baseline and post-intervention measurements were taken to assess changes in appearance and weight esteem. Compared to the controls, the intervention group yielded significant increases in both appearance ($p < .022$) and weight esteem ($p < .026$). The intervention group significantly increased in appearance esteem (from $M = 2.95$ to 3.15, $p < .001$, $d_z = 0.33$) and weight esteem (from $M = 3.16$ to 3.32, $p < .001$, $d_z = 0.27$), whereas the control group did not significantly change (appearance: $M = 2.72$ to 2.76, $p = .992$, $d_z = 0.13$; weight: $M = 3.01$ to 3.02, $p = .654$, $d_z = 0.06$) from baseline to post-intervention. No effects of gender were detected. Findings suggest that reducing SMU on smartphones may be a feasible and effective method of improving body image in a vulnerable population of youth.

Public Policy Relevance Statement

A brief 4-week intervention using screen time trackers showed that reducing social media use (SMU, experimental group) yielded significant improvements in appearance and weight esteem in distressed youth with heavy SMU, whereas unrestricted access to social media (control group) did not. Reducing SMU is a feasible method of producing a short-term positive effect on body image among a vulnerable population of users and should be evaluated as a potential component in the treatment of body image-related disturbances.

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This research received approval from Carleton University's research ethics board (Protocol 111107).

The data that support the findings of this study are available from the corresponding author upon reasonable request. The data are not publicly available due to ethics constraints and the potential for breaching participant privacy and confidentiality.

All participants provided were informed, orally and in writing, about the purpose of the study, its requirements, and potential risks involved as per the informed consent process. Participants who met the eligibility criteria provided informed consent.

As this research involved a brief social media reduction intervention that is still in the proof-of-concept stage, we did not deem this study as a clinical trial, therefore no registration was obtained. However, this research, involving human participants, conforms to the recognized standards of the Declaration of Helsinki and CONSORT Guidelines.

Helen Thai served as lead for data curation, formal analysis, visualization, writing–original draft, writing–review and editing and contributed equally to methodology. Christopher G. Davis served as lead for conceptualization, supervision. Wardah Mahboob served in a supporting role for project administration, writing–review and editing. Sabrina Perry served in a supporting role for project administration, writing–review and editing. Alex Adams served in a supporting role for project administration, writing–review and editing. Gary S. Goldfield served as lead for conceptualization, supervision. Helen Thai, Christopher G. Davis, and Gary S. Goldfield contributed equally to investigation. Christopher G. Davis and Gary S. Goldfield contributed equally to writing–review and editing.

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The rising popularity of social media use (SMU) has garnered attention over the last several years, with many concerned about the effects it may have on mental health, particularly in adolescents and young adults (Karim et al., 2020). Adolescence and young adulthood, spanning from ages 17 to 25 years, are critical stages of life during which numerous psychological, physical, neurobiological, behavioral, and social changes take place (Paus et al., 2008; Wood et al., 2018). These changes occur in concert with exposure to numerous sociocultural factors (e.g., appearance comparisons, teasing, social exclusion) that commonly perpetuate body dissatisfaction, a consistent predictor of eating disorders and other mental illnesses (Prnjak et al., 2021; Tremblay & Limbos, 2009). Paralleling this perpetuation of body dissatisfaction is the ubiquitous growth of SMU, which has undeniably become an integrated part of many young people's lives.

Although social media may indeed be an accessible medium for greater connectivity, resources, and creativity, many studies have documented that youth who are heavy or frequent users of social media tend to have more body image concerns (for meta-analysis, see Ryding & Kuss, 2020). However, evidence for the negative effect of SMU on body image is constrained by several limitations. To date, this literature is dominated by correlational studies that preclude or limit causal inferences and rely on self-reports to quantify SMU. Concerning self-reported time on social media, a recent meta-analytic review indicated that self-reported SMU correlates only weakly with device-based measures, suggesting that self-reported SMU does not adequately reflect actual use (Parry et al., 2021); device-based measures provide a more accurate assessment of SMU.[1] Moreover, few studies in the literature utilize an experimental design to assess the effects of SMU on body image (or, indeed, other aspects of mental health). Most experimental social media research on body image has involved implementing social media literacy programs among adolescent girls (Bell et al., 2022; McLean et al., 2017), or have focused on exposure to only certain social media platforms (e.g., Facebook; for review, see Fardouly & Vartanian, 2016).

In addition to these methodological criticisms, meta-analytic reviews of cross-sectional research on SMU and body image concerns have concluded that although statistically significant, the association is rather weak ($r = .169$; Saiphoo & Vahedi, 2019). This weaker-than-expected association between SMU and body image may be due to the possibility that some individuals are more vulnerable to the harmful effects of social media than others. For example, Seabrook et al. (2016) showed that youth with certain cognitive styles (e.g., ruminative, brooding) are more susceptible to the negative effects of SMU than those without those cognitive styles. Similarly, Twenge and colleagues have indicated that those lacking in-person interaction (Twenge, Joiner, et al., 2018) and/or those with preexisting mental health difficulties (Twenge, Martin, & Campbell, 2018) appear to be more susceptible to the negative effects of SMU than others. These studies suggest that distressed youth may be particularly vulnerable to the negative effects of frequent SMU; however, what has yet to be explored is whether reducing SMU would also reduce its potential harms.

To better understand the effect that reducing SMU has on body image, we conducted a pilot randomized controlled trial (RCT) wherein a sample of distressed, frequent (adolescent) users of social media were asked to limit their SMU to 60 min/day for 3 weeks (Thai et al., 2021). Compared to controls who self-monitoring controls who had unrestricted access to SMU, those asked to reduce their SMU showed improvements in appearance esteem but not weight esteem. However, due to the small sample size, we were unable to conduct meaningful gender analyses. The objective of this study is to replicate these results in a larger sample and to address these limitations to better understand the effects of reducing SMU on body image.

In this paper, we examine whether a brief intervention that targets SMU reduction (1 hr/day for 3 weeks) leads to improvements in facets of body esteem (i.e., appearance and weight esteem) in youth who experience emotional distress. Following our pilot study (Thai et al., 2021), we targeted a clinically relevant population as youth with distress are at greater risk of experiencing the negative effects of heavy SMU and are susceptible to significant body image concerns (Collison & Harrison, 2020). Accordingly, we hypothesized that participants in the intervention group, who were asked to reduce SMU to 1 hr/day, would exhibit greater improvements in both appearance and weight esteem at 4-week post-intervention compared to controls who had no restrictions on SMU. Given that females tend to experience greater body image concerns (He et al., 2020) and use social media more often than males (Keles et al., 2020), we also examined, as a secondary objective, the extent to which gender moderates the effect of SMU reduction on our outcome variables.

Method

Participants

Undergraduate students enrolled in an introductory psychology course at a Canadian university were recruited through an online participant pool to participate in a 4-week study entitled, *Limiting Social Media Screen-time on iPhones and Androids.* Participant recruitment took place over three academic semesters from January 2021 to December 2021. Eligibility requirements included individuals aged 17–25 years who were regular social media users (at least 2 hr/day on average) on their smartphones and have symptoms of depression or anxiety as assessed with two items from the Center for Epidemiological Studies Depression Scale (Bradley et al., 2010) and two items from the Generalized Anxiety Disorder Scale (Spitzer et al., 2006). The purpose of the study (i.e., examining the effects of limiting SMU on mental health-related outcomes) was not disclosed to participants during the recruitment, enrollment, and study period. All participants provided informed consent. This study received approval from the university's research

[1] Among the dearth of research using device-based measures of SMU is a recent prospective study by Sewall et al. (2022), which found that fluctuations in SMU over time did not affect psychological distress (depression, anxiety, social isolation) in young adults. This study, however, did not examine facets of body image, thus it is unknown whether changes in device-based measures of SMU would yield similar results for body image.

ethics board. Participants received grade-raising credit for their participation.

Study Design

The present study employed a parallel group, RCT design that was developed in compliance with CONSORT guidelines for non-pharmacological trials (Boutron et al., 2017). The 4-week study comprised a 1-week baseline period followed by a 3-week intervention period. Participants were randomly assigned to one of two groups, control or intervention, using a computer-generated randomization scheme on Excel by a member of the research team who was uninvolved in participant recruitment. Participants assigned to the intervention group were instructed to reduce their daily SMU to a maximum of 1 hr, whereas participants assigned to the control group were instructed to use their SMU as per usual (i.e., no restriction). Measurements were collected during pre- and post-intervention to detect changes in outcome variables.

Procedure

All study procedures were conducted virtually. Participant recruitment involved a rolling admission process, where the individual could enroll in the study and complete it in a given semester. After signing up to participate in the study, participants attended an online session (via Zoom) where they were informed, orally and in writing, about the purpose of the study, its requirements, and potential risks involved as per the informed consent process. Participants who met the eligibility criteria and provided informed consent were then instructed how to access and take a screenshot of their smartphone's daily screen time tracker to send to the study's secure email inbox daily over the 4-week study duration. Participants were then instructed to complete an online baseline questionnaire via Qualtrics, which contained demographic characteristics, mental health outcomes, and typical weekday and weekend SMU over the past week. During the baseline period (Days 1–7), all participants were instructed to use their SMU as per usual and received a daily email reminder each evening to send their SMU screenshot the next morning to capture the full 24 hr of the day. On Day 7, participants randomly assigned to the intervention condition received a daily email with instructions to reduce their SMU to a maximum of 1 hr/day starting the next day for the remaining three weeks (intervention period) and to send their SMU screenshot, while those in the control group received the same daily email sent during the baseline period reminding them to send their SMU screenshot (i.e., controls were not instructed to limit SMU). In the case that a participant in the intervention group did not reduce their SMU to a maximum of 1 hr/day, an email was sent to remind them of the study procedure. On Day 28, all participants received the post-intervention questionnaire to complete via Qualtrics. Upon study completion, an electronic debrief form was provided to inform participants of the purpose of the study (i.e., to evaluate the effects of reducing SMU on mental health).

Measures

Basic demographic information was collected at baseline via online questionnaires, which included age (in years) and gender categories (female, male, and other). Although the focus of this paper is on the effect of SMU on body esteem variables, data on other mental health outcomes (i.e., depression, anxiety) were also collected but have been reported elsewhere as they were the primary outcomes of this study (Davis et al., n.d.).

Social Media Use

Daily SMU was tracked objectively using screenshots of integrated smartphone screen time tracking reports that were submitted to the study's secured inbox over the study period.[2] The integrated screen time reports allow for tracking time spent on individual platforms. Social media platforms tracked in this study included Facebook, Instagram, Tik Tok, Snapchat, Twitter, Pinterest, and Tumblr. Messaging, video-calling, and -streaming platforms, such as Facebook Messenger, WhatsApp, FaceTime, YouTube, and Netflix, were not tracked or targeted for reduction. Using device-based measures of SMU increases reliability and eliminates the risk of recall bias common in self-reports of behavioral activity (Parry et al., 2021).

Appearance and Weight Esteem

Levels of appearance and weight esteem were measured using an abbreviated version of the Body Esteem Scale for Adults and Adolescents (BESAA; Mendelson et al., 2001). The original BESAA is divided into appearance, weight, and attribution subscales. We assessed appearance and weight esteem using the five of the highest loading items based on Cragun et al.'s (2013) factor analysis for appearance (e.g., "I'm pretty happy about the way I look") and weight (e.g., "I am satisfied with my weight") esteem subscales. An a priori decision was made to exclude the attribution subscale as items pertaining to this subscale focused on evaluation attributed to *others* about one's appearance and body (e.g., "People my own age like my looks"). Responses to appearance and weight esteem subscale items were made on a 5-point Likert scale ranging from 1 (*never*) to 5 (*always*). After reverse scoring 6 out of the 10 items, a mean item score was calculated for each subscale, with higher scores indicating higher esteem. In the present study, Cronbach's αs at baseline were 0.90 and 0.88, and at post-intervention were 0.90 and 0.90 for appearance and weight esteem, respectively.

Analytic Plan

Data for outcome variables were approximately normally distributed in accordance with skewness and kurtosis standards indicated by Byrne (2013) and Hair et al. (2010). Descriptive statistics were used to characterize the sample at baseline. Group differences were evaluated by independent t tests for continuous data and

[2] We also asked participants in the initial survey and follow-up survey to self-report using a slider (range: 0–10+ hr) their average daily SMU on other devices (e.g., laptop, tablet) in the past week. However, these questions had a great deal of missing data, perhaps because the slider was initially set to zero and participants may have assumed that leaving it at zero indicated 0 hr on other devices. If they did not move the slider, the program registered it as a skipped question. Given that we cannot determine whether a non-response should be coded as "0 hr" or "missing data/skipped question," we do not report these data.

chi-square tests for categorical data. To ensure the intervention was successful in limiting participants' SMU, a 2 (condition) × 4 (week) mixed analysis of variance (ANOVA) was conducted as a manipulation check to compare daily SMU among participants in each condition during the 4-week study period. To test whether the intervention had effects on appearance and weight esteem, and if intervention effects were moderated by gender, separate 2 (condition) × 2 (pre, post) × 2 (gender: male/female) mixed ANOVA models were conducted for each outcome. Significant interactions were explored via simple effects. Statistical power was calculated using GLIMMPSE Version 3 software (Kreidler et al., 2013). Power was estimated based on a hypothesized condition × time interaction using a repeated ANOVA to determine the requisite sample size to detect an expected 1/3 *SD* change in our outcome variables in the intervention group, whereas no change was expected in the control group, and anticipating a test–retest correlation in dependent variables of $r = .6$. For power of 0.80, 200 participants were required. For all analyses, an α value was set at 0.05 to determine significance. Cohen's d was used as a measure of effect size where 0.2, 0.5, and 0.8 are considered small, medium, and large effect sizes, respectively (Cohen, 2013). Data were analyzed using SPSS Version 28.

Results

Descriptive Statistics

A total of 279 participants (76% female, 23% male, and 1% other) were recruited and met the eligibility criteria. Sixty-seven percent were aged 17–19 years, 20% were 20–22 years, and 13% were 23–25 years. Of the 279 participants, 59 were excluded from the analyses. A summary of participants included in the analyses is outlined in the CONSORT diagram (Figure 1). The baseline characteristics of the remaining sample are described in Table 1. Participants demonstrated strong compliance in providing screenshots of their daily SMU over the baseline and intervention periods and did not differ by group ($p \geq .71$). During the baseline period, 94.5% provided screenshots on all 7 days and 93.2% provided screenshots on at least 20 days during the intervention.

Manipulation Check

Results of the mixed ANOVA revealed that the intervention was successful at reducing participants' daily SMU, $F(3, 648) = 94.05$, $p < .001$, $d = 1.31$. Simple effects showed no difference between groups during the baseline period, $p = .197$, however, significant differences were detected between groups during the 3-week intervention period, $p < .001$. Participants in the intervention condition reduced their daily SMU by approximately 50%, to an average of 78.25 min/day (relative to 168.04 min/day during baseline), whereas those in the control group averaged 180.81 min/day and 188.76 min/day during the baseline and intervention period, respectively.

Main Analyses

For appearance esteem, results of the mixed ANOVA indicated a nonsignificant main effect of condition, $F(1, 213) = 1.03$, $p = .311$, $d = 0.02$, a significant main effect of time, $F(1, 213) = 5.40$, $p = .021$, $d = 0.29$, and a significant condition by time interaction, $F(1, 213) = 5.33$, $p = .022$, $d = 0.28$. Simple effects revealed that the intervention group significantly increased in levels of appearance esteem (from $M = 2.95$ to 3.15, $p < .001$, $d_z = 0.33$),[3] whereas the control group did not significantly increase (from $M = 2.72$ to 2.76, $p = .992$, $d_z = 0.13$) from baseline to post-intervention (see Figure 2). When gender (male/female) was added as an independent factor to the model, a significant main effect of gender was detected, $F(1, 213) = 8.42$, $p = .004$, $d = 0.37$, however, gender did not significantly moderate the two-way interaction, $F(1, 213) = 3.50$, $p = .063$, $d = 0.21$.

For weight esteem, mixed ANOVA results indicated a significant main effect of condition, $F(1, 213) = 8.34$, $p = .004$, $d = 0.37$, significant main effect of time, $F(1, 213) = 8.35$, $p = .004$, $d = 0.37$, and a significant condition by time interaction, $F(1, 213) = 5.04$, $p = .026$, $d = 0.27$. Simple effects revealed that the intervention group significantly increased in levels of weight esteem (from $M = 3.16$ to 3.32, $p < .001$, $d_z = 0.27$), whereas the control group did not increase significantly (from $M = 3.01$ to 3.02, $p = .654$, $d_z = 0.06$; see Figure 3). The main effect of gender (male/female) was not significant, $F(1, 213) = 1.16$, $p = .282$, $d = 0.06$, nor did gender moderate the two-way interaction described above, $F(1, 213) = 1.91$, $p = .168$, $d = 0.13$. See Table 2 for a summary of ANOVA main and interaction effects on outcome variables.

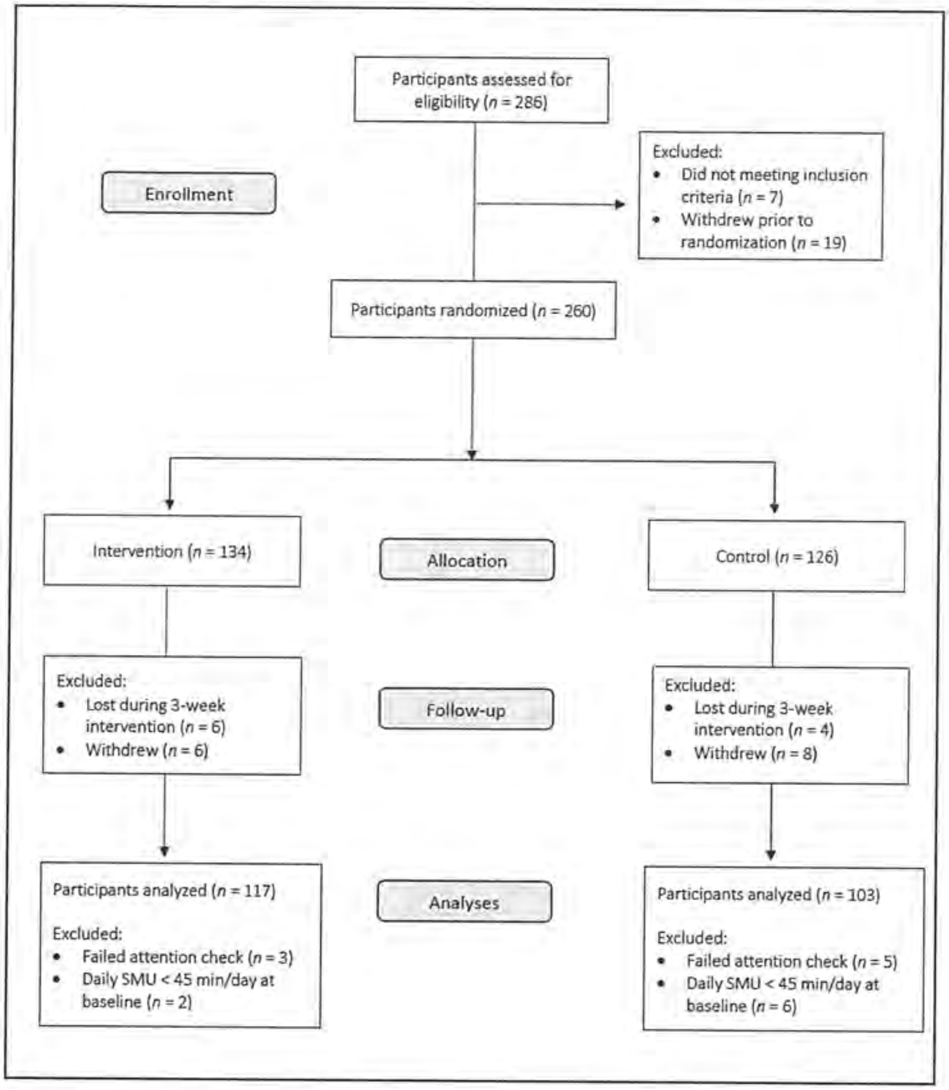
Discussion

The present study examined the effect of reducing SMU on appearance and weight esteem in youth with emotional distress. Results supported our hypothesis that reducing daily SMU led to discernible improvements in both appearance and weight esteem relative to self-monitoring controls who had unrestricted access to SMU. Notably, the intervention group exhibited significant improvements in appearance and weight esteem, with small to medium effect sizes. Moreover, exploratory moderation analyses showed that, within our sample, reducing SMU may have a positive effect on body image that is comparable for both male and female youth with emotional distress. By utilizing an experimental design and assessing SMU through an integrated device-based measure, these findings overcome the most significant limitations of prior studies and advance knowledge on whether reducing SMU facilitates improvements in body image among youth with emotional distress.

Although potential mechanisms driving this effect were not investigated in the present study, researchers have proposed that limiting SMU may reduce users' engagement in unfavorable social comparisons and ideal body internalization, thereby facilitating improvements in appearance and weight-related esteem (Fardouly et al., 2015; Hogue & Mills, 2019; Jarman et al., 2021; Marengo et al., 2018; Tiggemann et al., 2018). For example, one recent study found that upward social comparison with social media influencers fully mediated the relation between Instagram use and body dissatisfaction among female youth (Pedalino & Camerini, 2022). However, a large proportion of such studies are based on cross-sectional data, self-reported SMU, and do not consider individual

[3] The effect size estimate Cohen's d_z was calculated directly from the t value and number of participants using the formula provided by Lakens (2013).

Figure 1
Participant CONSORT Flow Diagram



differences that make some youth more susceptible than others. As such, there is a need for more experimental research to better understand *how reducing* SMU confers improvements in body esteem in vulnerable populations, such as youth with emotional distress who are heavy users of SMU.

Limitations

Although the present study adds experimental evidence to the extant literature on the effect of modifying SMU on body image, there are limitations to consider. First, the intervention was brief (3 weeks long) and may not be effective if extended for a longer duration for youth who are heavy SMU users. Nonetheless, both participant compliance and retention to the intervention were high and provide support as a proof-of-concept study. Second, it remains unknown the extent to which those in the intervention condition would be able to maintain the reduced SMU beyond the study period and if long-term reduction in SMU would yield stronger improvements. Third, although not all participants in the intervention group met the 1 hr/day SMU limit, SMU was reduced by approximately 50% during the 3-week intervention period (~78.25 min/day) from baseline (~168.04 min/day). This suggests that, for some heavy users, reducing SMU to 1 hr/day may not be overly ambitious. That the intervention group reduced SMU by 50% and still showed improvement in body image suggests that it is the reduction in time spent on social media that is important.

Although we were able to objectively monitor SMU on smartphone devices, we had no control over SMU that may have occurred on other devices (e.g., computers, tablets, and laptops). It is unlikely that those participants assigned to the intervention condition disproportionately shifted their use to other devices since if they had

Table 1
Baseline Characteristics of Study Sample

Variables	Total, $N = 220$	Intervention, $n = 117$	Control, $n = 103$	p
Gender (n)				.55
Male	50	25	25	
Female	168	92	76	
Other	2	0	2	
Age group (n)				.39
17–19 years old	161	84	77	
20–22 years old	37	22	15	
23–25 years old	11	4	7	
Baseline variables M (SD)				
Appearance esteem	2.85 (0.88)	2.95 (0.85)	2.72 (0.90)	.06
Weight esteem	3.09 (1.07)	3.16 (1.08)	3.01 (1.06)	.28
Daily social media use (Days 1–7)	174.02 (76.32)	168.04 (73.01)	180.81 (79.74)	.11

Note. $p < .05$ to indicate differences between intervention and control.

done so, we would not have observed the improvements in body image.[4]

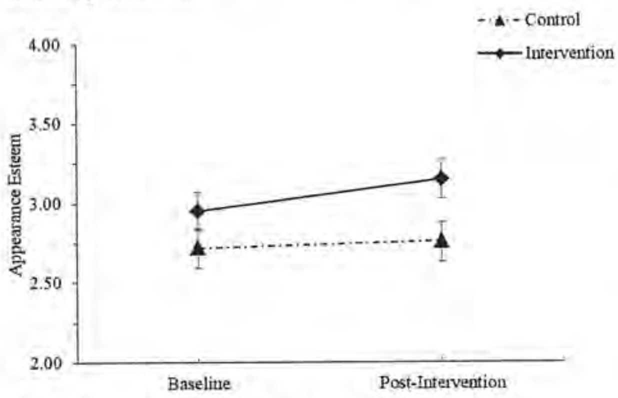
Whereas one of our goals was to assess gender differences in the extent to which reducing social media improves body image, our sample was still disproportionately female (3:1). Although this is to be expected given (a) that psychology students are more likely to be female than male, and (b) that females were more likely than males to meet eligibility criteria (i.e., report symptoms of depression or anxiety and be heavy users of social media), it nevertheless means that our analyses involving gender were somewhat underpowered.

Finally, it must be acknowledged that our sample comprised university students who volunteered to enroll in a study where they had a 50/50 chance of being asked to reduce their SMU, and as such, the results may not generalize to youth less motivated to limit their SMU.

Future Directions

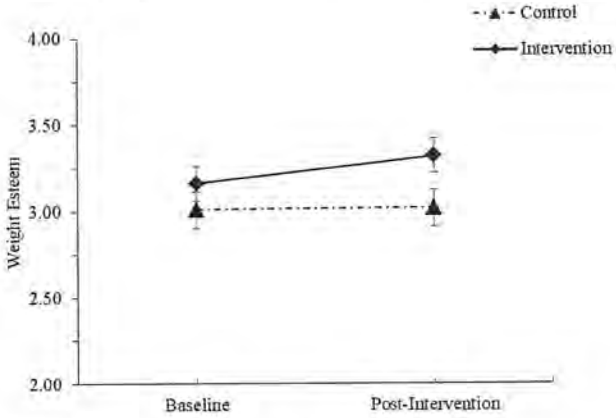
The present study targeted a vulnerable population (i.e., youth with emotional distress who use social media frequently) that may be at greater risk of body image concerns, thus providing greater clinical relevance and utility of the intervention. Although there is good evidence that high SMU may perpetuate body image concerns, an important avenue for future research is to clarify not just *who* is at risk of social media harms, but also *what* kind of use is likely to lead to harm if users are engaging with certain content. Most social media platforms are developed in such a way that users' daily social media feed is generated by the algorithms based on their engagement with specific content and/or sources (e.g., models, peers, businesses, memes). In other words, the content to which users are exposed may influence facets of body image differently. For instance, SMU on visual-based platforms such as Instagram was found to predict users' visual attention to high-anxiety body regions to a greater extent than platforms that often display both visual and word-based posts, such as Facebook (Couture Bue, 2020). Future research may benefit from investigating other aspects of SMU in addition to time spent on these platforms.

Figure 2
Effect of Reducing Social Media Use on Levels of Appearance Esteem by Condition



Note. Error bars represent standard errors.

Figure 3
Effect of Reducing Social Media Use on Levels of Weight Esteem by Condition



Note. Error bars represent standard errors.

Conclusion

The present study makes a novel contribution to the limited experimental literature on SMU and body image. To the best of our knowledge, this is the first adequately powered study to demonstrate that a brief intervention involving smartphone-based SMU reduction of approximately 50% from baseline may be a feasible and effective method of improving appearance and weight esteem among youth with emotional distress. Our findings show that reducing SMU reaps comparable benefits in body esteem for both males and females. Although more research is warranted to assess maintenance effects, our findings show that reducing SMU has a short-term positive effect on body image among a vulnerable population of youth with emotional distress, and thus should be evaluated as an important component in the treatment and prevention of body image-related disturbances.

[4] As noted earlier, at our 4-week follow-up assessment, we did ask participants in both conditions the extent to which they used other devices in the past week. Although there were data quality issues, we found no significant difference between those in the intervention and those in the control conditions.

Table 2

ANOVA Main Effects and Interaction Effects on Appearance and Weight Esteem

Source	*MS*	*F*	*p*	*d*
Appearance esteem				
Condition	2.18	1.03	.311	0.02
Time	**0.81**	**5.40**	**.021**	**0.29**
Gender	**17.78**	**8.42**	**.004**	**0.37**
Condition × Time	**0.80**	**5.33**	**.022**	**0.28**
Condition × Gender	1.33	0.63	.43	0.00
Time × Gender	0.00	0.03	.868	0.00
Condition × Time × Gender	0.52	3.50	.063	0.22
Error (within)	0.15			
Error (between groups)	2.11			
Weight esteem				
Condition	**12.11**	**8.34**	**.004**	**0.37**
Time	**1.18**	**8.35**	**.004**	**0.37**
Gender	2.66	1.83	.178	0.12
Condition × Time	**0.71**	**5.04**	**.026**	**0.27**
Condition × Gender	1.69	1.16	.282	0.06
Time × Gender	0.03	0.18	.676	0.00
Condition × Time × Gender	0.27	1.91	.168	0.13
Error (within)	0.14			
Error (between groups)	1.45			

Note. Boldface indicates statistical significance ($p < .05$); $N = 218$.

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To detox or not to detox? The impact of different approaches to social media detox strategies on body image and wellbeing

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Keywords:
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Wellbeing

ABSTRACT

This study compared the efficacy of three 7-day detox strategies on young women's body image and wellbeing. The three strategies were: (a) Insta/TikTok break, (b) daily time-cap (30 minutes max), and (c) Insta/TikTok cleanse (removing appearance-focused content from feeds). A sample of 175 women aged 17–35 ($M = 22.71$) was randomized into one of the three detox conditions or social media use as usual. Participants completed assessments of self-objectification, appearance satisfaction, body appreciation, media pressure, and wellbeing at baseline, day 3 (check-in) and day 7 (posttest). Significant interactions showed that appearance satisfaction improved for all three detox groups from baseline to posttest, but no changes occurred for the control group. Appearance satisfaction also increased from day 3 to posttest in the Insta/TikTok cleanse group. Wellbeing improved from baseline to posttest for the daily time-cap group. Increases in wellbeing also occurred from day 3 to day 7 for the Insta/TikTok break and daily time-cap groups. No further interactions were found. Findings shed light on the varying effects of three 7-day social media detox strategies for promoting appearance satisfaction and overall wellbeing. ... t emerged as a particu-
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DEPRIVATION
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1. Introduction

The popularity of social media applications (apps) among young women is well documented (Dixon, 2024). High school and college educated women aged 18–34 are the highest demographic of users for apps such as Facebook, Instagram, TikTok and YouTube (Pew et al., 2024) with an average user time of 2.5 hours per day compared to within other age groups (Kemp, 2024). Although young women use social media for connection, top platforms like Instagram and TikTok (Pew et al., 2024) emphasize appearance-focused content, promoting unrealistic beauty ideals like flawless skin and a lean physique (Tylka et al., 2023). Extensive research shows that high consumption of appearance-focused content on social media may lead to higher levels of self-objectification (viewing oneself as an object to be admired) and body dissatisfaction (Tylka et al., 2023), as well as lower appreciation and respect for one's body (e.g., Duan et al., 2022; Garcia et al., 2022). Increased screen time on such apps may also lead to lower levels of wellbeing (i.e., a state of feeling healthy, happy, and fulfilled in life), a factor that is intertwined with body image issues (Hicks et al., 2022; Lambert et al., 2022). These findings are particularly concerning given that the proliferation of appearance-focused apps has coincided with the rise in eating and body dysmorphic disorders among young women (Dondzilo et al., 2024; Fellows, 2023; Laughter et al., 2023). Consequently, identifying strategies to mitigate the adverse effects of social media use on young women's body image and wellbeing is essential.

One strategy gaining traction in mainstream media is the promotion of a digital detox to improve overall wellbeing and address mental health concerns stemming from prolonged digital media consumption

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(e.g., Breen, 2021). According to Radkte et al. (2022), the term digital detox refers to a duration wherein individuals voluntarily and intentionally refrain from using devices, social media applications, branded media, interactive features, and viewing or replying to messages. Despite their increasing popularity, evidence regarding the benefits of social media detoxes on one's overall wellbeing is mixed, likely due to variations in detox duration and type (Radtke et al., 2022). Moreover, while there are established links between social media use and body image, there remains a dearth of research investigating the impact of social media detoxes on body image (e.g., Smith et al., 2024; Thai et al., 2023). Notably, prior studies (e.g., Fioravanti et al., 2021; Hunt et al., 2018) have typically focused on examining the effects of one detox strategy on wellbeing and body image, such as abstinence or imposing a daily time limit. This narrow focus, which neglects the active avoidance of potentially detrimental content through digital pruning or cleansing, limits our comprehension of how different detox strategies may or may not impact upon body image and wellbeing, and which may be more effective. Understanding these variations is crucial for offering individuals a range of options that could effectively aid in a digital detox. The aim of this study was to conduct a randomized controlled trial on the efficacy of three types of 7-day social media detox strategies (abstinence, daily time limit, and cleanse) on young women's self-objectification, appearance satisfaction, body appreciation, internalized media pressure, and wellbeing. To our knowledge, this is the first study to directly compare these different detox strategies.

1.1. *Appearance-related social media*

Appearance-related content on social media refers to any posts, images, videos, or discussions that primarily focus on physical appearance. This type of content can include outfit of the day posts, makeup/skincare tutorials (get ready with me; #GRWM), fitness progress updates, cosmetic procedure journeys, curated selfies, and discussions about weight (see Tylka et al., 2023). The intersection of appearance-related content and influencer culture has become increasingly prominent highlighting how influencers often shape beauty standards and trends through their posts (Kasumovic, 2024). Young women continue to dominate this space, commanding a substantial 70 % market share. Notably, Instagram and TikTok emerge as the frontrunners in this arena, each capturing 42 % of the market share. Marketing data further underscore the prevalence of influencer engagement among women aged 16–34, with one third actively following influencers, compared to one quarter of men in the same age group (Thorpe, 2024). In terms of content niches, half of the top 10 influencer categories searched for on Instagram and TikTok are appearance-focused, including fashion, beauty, health and fitness, lifestyle, and modelling (Kasumovic, 2024). Similarly, teenage girls and young adult women are more likely to use photographic filters on selfies they post to social media compared to males and older adults (Dhir et al., 2016). These findings provide a clear picture of the prevalence of appearance-related content within the social media landscape, particularly among female audiences, and the platforms driving this engagement.

Notably, the algorithm of social media platforms is the primary mechanism through which young women's feeds are inundated with appearance-related content. Designed to enhance the user experience by showing the most relevant and engaging content first, algorithms are also constantly evolving based on the user's past behavior, the behavior of those they follow or engage with, and even the time of day they use the app (AIContentfy, 2024). User engagement, marked by likes, comments, shares, and views, plays a pivotal role in how social media algorithms prioritize content. However, emphasis on user engagement can be detrimental, incentivizing content creators to produce posts aimed at evoking emotional reactions (AIContentfy, 2024). For example, when content promoting idealized appearance garners significant engagement, it is likely to be propagated to other young women as high-priority or valuable content, which may elicit emotional or evaluative responses from those who feel their appearance falls short in comparison. Consequently, it is imperative to explore how young women can adeptly navigate, or take a break from, social media platforms to safeguard their body image and wellbeing.

1.2. *Body image and appearance-related social media*

The tripartite influence model (Thompson et al., 1999) and objectification theory (Fredrickson & Roberts, 1997) are two sociocultural frameworks that have been instrumental in understanding the development and maintenance of negative body image (Thompson et al., 1999). The tripartite influence model proposes that body dissatisfaction stems from societal pressures exerted by family, peers, and media to attain the culturally idealized lean and toned physique. Among these influences, media (and now social media) has been identified as the most pervasive source of body dissatisfaction, primarily due to its capacity to disseminate idealized imagery (Grabe et al., 2008; Vandenbosch et al., 2022) and consistently portray an unrealistically thin, fit, and toned ideal (Tiggemann & Zaccardo, 2015). Objectification theory offers a framework for understanding the implications of living in a society where women's bodies are frequently evaluated. Notably, media (traditional and social) that depicts women as submissive to men or as objects to be evaluated (e.g., perfume and fashion ads) is a significant contributor to the pressures faced by women to maintain an attractive appearance (Daniels et al., 2020). Over time, women may come to experience varying degrees of self-objectification where they prioritize appearance attributes over personal characteristics like competence, potentially triggering a chain of negative events such as body surveillance (i.e., body checking behaviours), appearance anxiety, and body shame (Fredrickson & Roberts, 1997).

Regardless of whether young women view idealized appearance-focused images or videos on social media, this content can reinforce the importance of appearance and lead to body dissatisfaction and self-objectification (Gurtala & Fardouly, 2023). Content analyses show that between a third and half of the content on TikTok and Instagram promotes negative body image messages such as weight loss and objectification (Lucibello et al., 2021; Raiter et al., 2023). Similarly, greater photo investment in selfies was found to be linked with self-objectification and inversely related to body satisfaction among predominantly undergraduate women (Cohen et al., 2018). Experimental studies further support these patterns. Pryde and Prichard (2022) found that body dissatisfaction increased among women after brief exposure to TikTok fitspiration videos compared to art videos. Similarly, undergraduate women reported increases in body dissatisfaction following exposure to celebrity and peer images on Instagram compared to travel images (Brown & Tiggemann, 2016), while Lowe-Calverly and Grieve (2021) revealed that images of idealized influencers (regardless of their popularity) led to greater body dissatisfaction compared to nature images. Moreover, Seekis and Kennedy (2023) found that undergraduate women who viewed just seven minutes of beauty content on TikTok experienced higher appearance anxiety and shame compared to those who viewed self-compassion or travel content.

In addition to the well-established negative impact of idealized appearance content on young women's body image, engagement with this content on social media has also been linked to lower positive body image (see Tylka et al., 2023). Positive body image is characterized by a comprehensive love, respect, and appreciation for one's body and its functions (Tylka & Wood-Barcalow, 2015), typically assessed as body appreciation. Correlational studies have shown that frequent engagement with appearance-related content on platforms like Instagram is linked to lower body appreciation (Duan et al., 2022; Peadlino & Camerini, 2022). In support, undergraduate women reported decreased body appreciation after exposure to Instagram images of attractive celebrities compared to travel images (Brown & Tiggemann, 2020). Together, these findings highlight the potential harm that consuming idealized appearance-focused imagery and videos on platforms like

Instagram and TikTok can inflict on young women's body image.

Notably, not all appearance-focused content on social media negatively affects body image. For instance, studies suggest that exposure to body positivity social media content (Cohen et al., 2019) and more recently, body neutrality social media content (Seekis & Lawrence, 2023), can improve young women's body satisfaction. Despite these findings, concerns have been raised about the objectification present in some body positivity posts with research indicating that such content can increase self-objectification in young women (Cohen et al., 2019). Since appearance remains a central focus in both idealized and body positive content, it is important to investigate whether taking short breaks from appearance-focused apps, reducing time spent on these platforms, or temporarily cleansing one's feed of appearance-related content could positively impact young women's self-objectification.

1.3. Social media detoxes

Given the substantial evidence of a negative relationship between highly visual social media use and various aspects of wellbeing (e.g., Jarman et al., 2021; Lambert et al., 2022), it is unsurprising that specific interventions aimed at digital detox, such as temporarily deactivating accounts or limiting social media usage, have gained popularity (Radtke et al., 2022). According to WHO (2021), wellbeing includes both quality of life and the ability to contribute to society with a sense of meaning and purpose. However, activities like posting, tagging, and liking others' content on Facebook have been linked to reduced wellbeing (Shakya & Christakis, 2017; Vigil & Denis Wu, 2015), while daily Instagram use has been associated with lower daily life satisfaction (Garcia et al., 2022).

Although disconnecting from or reducing time spent on social media might appear beneficial for one's wellbeing, research findings are mixed (Radtke et al., 2022). For instance, studies have demonstrated that a 1-week abstinence from social media enhanced wellbeing (Brown & Kuss, 2020; Lambert et al., 2022), with Fioravanti et al. (2020) specifically noting increased life satisfaction among women following a 7-day disconnect from Instagram. Similarly, imposing a 2-week daily limit of 30 minutes on all social media platforms resulted in higher reported life satisfaction and perceived wellbeing among a sample of undergraduates (Coyne & Woodruff, 2023). In addition, limiting daily usage of Facebook, Instagram, and Snapchat to 10 minutes per platform showed improvements in elements of wellbeing such as loneliness (Hunt et al., 2018). However, other studies have found no significant change in life satisfaction after a 7-day abstinence from Facebook and Instagram (Hanley et al., 2019); in fact, Hall et al. (2021) indicated that varying durations of abstinence (1–4 weeks) from social media had no effect on wellbeing. Furthermore, some studies have shown decreases in wellbeing following abstinence from social media (Radtke et al., 2022; Wadsley & Ihssen, 2023), perhaps due to feelings of disconnection from peers. Consequently, the evidence remains inconclusive regarding the efficacy of social media abstinence or daily time constraints on overall wellbeing.

Despite the limited studies investigating the impact of social media detoxes on young women's body image, emerging findings are promising. For instance, Roberts et al. (2022) found that pre- and teenage girl dancers reported improvements in self-objectification following a 3-day social media fast. Among undergraduates with elevated levels of social media use, depression, and symptoms of anxiety, reducing social media use to 1-hour per day for 3 weeks led to significant improvements in appearance and weight esteem, with small to medium effect sizes (Thai et al., 2023). Most recently, Smith et al. (2024) found that a 7-day meaningful break comprising abstinence or restricted access from social media led to higher body satisfaction relative to those who continued to use social media as usual.

Digital pruning or cleansing has currently emerged as an alternative detox strategy. This method refers to a deliberate and thoughtful approach to using social media, in which individuals actively avoid detrimental content by unfollowing, blocking, or muting accounts and users (Hockin-Boyers et al., 2021). Findings from qualitative research involving young female weightlifters in recovery from eating disorders showed that weeding out harmful social media trends that promote diet culture (e.g., skinny teas) and unrealistic beauty standards assisted participants with reducing unfavorable emotions and a negative state of mind (Hockin-Boyers et al., 2021). Initiatives like Dove's #DetoxYourFeed offer promising approaches to safeguard young people from the adverse effects of consuming appearance-focused social media. However, research has yet to determine the impact of cleansing social media feeds on body image and wellbeing.

1.4. The current study

The overall aim of this study was to expand upon the current, but limited, research by evaluating the efficacy of three types of 7-day detox strategies, relative to a control, on young women's body image and wellbeing. A period of 7 days was chosen based on prior research (e.g., Fioravanti et al., 2020) and to maximise retention. The four conditions across the 7-day duration were: (a) abstinence from Instagram and TikTok (Insta/TikTok break), (b) 30-minute daily time limit across all photo-based social media apps which included Instagram, TikTok, Snapchat, and Facebook (daily time-cap), (c) cleansing appearance focused content from feeds on Instagram and TikTok (Insta/TikTok cleanse) and, (d) social media use as usual (control). The 30-minute daily time limit was based on the limits set by prior studies (Coyne & Woodruff, 2023; Hunt et al., 2018). Given the focus of this study, Instagram and TikTok were chosen for the break and cleanse conditions because both platforms are mostly consumed by women aged 18–34 (Pew et al., 2024). They are also appearance-centric and thus provide more scope for cleansing one's feed and taking a break from the plethora of idealized content. Additionally, some studies have shown that abstinence from all social media apps may be detrimental to one's wellbeing (Wadsley & Ihssen, 2023).

Based on prior research (e.g., Lambert et al., 2022; Roberts et al., 2022; Thai et al., 2023) and the likelihood that a social media detox strategy may minimize media pressure and foster a sense of body appreciation given the negative effects of appearance-focused social media on body image (see for review, Fioravanti et al., 2022), the following hypotheses were formulated. It was predicted that the pattern of change over time would differ by group. Specifically, it was predicted that improved outcomes in self-objectification, media pressure, appearance satisfaction, body appreciation, and wellbeing from baseline to T3 (day 7) would be found in the three detox groups while the control group would report no change. It was also expected that the detox groups would demonstrate improved outcomes from T2 (day 3) to T3 (day 7) while the control group would show no change. No hypotheses were formed regarding which detox group would show the most change, leaving this to be explored as a general research question.

2. Method

2.1. Participants

The final sample comprised 175 women aged 17–35 years (M_{age} = 22.71, SD = 5.45), 71 % of whom were undergraduates and 29 % community participants. About 70 % of participants identified as White, 19 % as Asian, 4 % as Australian Aboriginal, and 7 % as Other (e.g., African, Middle Eastern, Pacific islander).

2.2. Measures

2.2.1. Demographics

Participants were asked to report their age, gender, and ethnicity. They also self-reported daily time spent on social media apps as well as the type of content they most frequently viewed or followed. Height and weight were also self-reported to calculate body mass index (BMI).

2.2.2. Self-objectification

The 14-item Self-Objectification Beliefs and Behaviours Scale (SOBBS; Lindner & Tantleff-Dunn, 2017) was used to measure self-objectification. As sample items is, (*"How I look is more important to me than how I think or feel"*). Scores range from 1 *(strongly disagree)* to 5 *(strongly agree)* and are averaged such that higher scores reflect greater self-objectification. Lindner and Tantleff-Dunn (2017) reported high internal consistency (α =.90) and excellent test-retest reliability (r = .89). Internal consistency for the current study was also high at Time 1 (α =.91), Time 2 (α =.92), and Time 3 (α =.93).

2.2.3. Appearance satisfaction

To assess appearance satisfaction, the 7-item Appearance Evaluation subscale of the Multidimensional Body-Self Relations Questionnaire (MBSRQ; Cash, 1990) was used. An example statement is, (*"I like my looks just the way they are"*). The subscale assesses individuals' satisfaction or dissatisfaction with their overall appearance with scores ranging from 1 (*definitely disagree*) to 5 (*definitely agree*). After reverse scoring two items, scores were averaged whereby higher appearance evaluation scores indicate greater satisfaction and a positive regard for one's appearance (Cash, 1990). Brown et al. (1990) reported high internal consistency (α =.88) among a sample of undergraduate students. Internal consistency was also high in the current study at Time 1 (α =.88), Time 2 (α =.90) and Time 3 (α =.88).

2.2.4. Body appreciation

The 10-item Body Appreciation Scale-2 (BAS-2; Tylka & Wood-Barcalow, 2015a) was used to measure body appreciation. An example item is, (*"I respect my body"*). Scores range from 1 *(never)* to 5 *(always)* and are averaged with higher scores representing higher body appreciation. The authors reported high internal consistency (α =.93) and test-retest reliability at 3 weeks (r = .90) among a sample of undergraduate students (Tylka & Wood-Barcalow, 2015a). Internal consistency was also high in the current study at Time 1 (α =.95), Time 2 (α =.95) and Time 3 (α =.96).

2.2.5. Media pressure

The Media Pressures subscale from the Sociocultural Attitudes Towards Appearance Questionnaire (SATAQ-4; Schaefer et al., 2015) was used to assess social media's perceived pressure to achieve social and cultural beauty ideals. The items were prefaced by a statement asking participants to consider their responses within the context of social media use. An example item is, (*"I feel pressure from the media to look in better shape."*). Responses range from 1 (*definitely disagree*) to 5 (*definitely agree*). Scores were averaged with higher scores demonstrating higher social media pressure. The authors reported excellent internal consistency for the subscale (α =.95) and convergent validity was shown via positive associations with eating disorder symptomatology and negative associations with body satisfaction (Schaefer et al., 2015). Internal consistency for the current study was high at Time 1 (α =.93), Time 2 (α =.93), and Time 3 (α =.91).

2.2.6. Wellbeing

Wellbeing was measured using the World Health Organisation (1998) five-item Wellbeing Index (WHO-5). A sample item is (*"I have felt cheerful and in good spirits"*). Responses ranged from 0 (*at no time*) to 5 (*all the time*). Scores were summed and ranged from 0 to 25, where 0 indicated the worst possible and 25 indicated the best possible quality of life. Topp et al. (2015) showed the scale to have good internal consistency (α =.81). Internal consistency for the current study was high at Time 1 (α =.89), Time 2 (α =.88), and Time 3 (α =.93).

2.2.7. Attention and filler items

Three attention check items (e.g., *for this item please select "Agree"*) were included to capture participants who were not responding with due diligence. Participants who failed two out of three attention checks for any of the timepoints were excluded from the study (see Muszyński, 2023).

2.3. Procedure

Following approval from three Institutional Ethics Committees, the study was pre-registered (https://aspredicted.org/8VM_ZK6) prior to commencement of data collection.

Data were collected via first year psychology participant pools, campus flyers, and paid Facebook advertisements between July and December 2023. Eligible participants were women aged 17–35 years who had, at minimum, an Instagram or TikTok account. Owing to the constraints imposed by time limit settings, only participants who reported using an iPhone were considered eligible for the partial detox condition, resulting in 67 % of the sample being eligible for randomization into that group. The study was conducted online via Qualtrics. Participants read an information package and were deemed to have consented upon commencement of the baseline survey. Participants could withdraw from the study at any time without incurring penalty. The average completion time for each survey was 21.36 minutes. Upon completion of each wave, undergraduate participants were redirected to a separate link for course credit. All participants were offered entry into a prize draw for one of six $50 gift vouchers.

Following informed consent, participants completed measures of self-objectification, appearance satisfaction, body appreciation, media pressure, and wellbeing at Time 1 (baseline), Time 2 (day 3) and Time 3 (day 7). All measures were randomized to minimize practice effects. They also completed demographic questions on age and social media use at baseline. Upon completion of the baseline measures, Qualtrics randomly assigned participants to one of four groups (Insta/TikTok break, daily time-cap, Insta/TikTok cleanse, or control [social media use as usual]) and each group was provided with a specific set of instructions. Participants assigned to one of the three detox conditions were instructed to begin the assigned detox within 24 hours of completing the baseline questionnaire whereas those assigned to the control condition were asked to continue social media use as usual. Text messages that included a link to the next survey were automatically sent to participants at Time 2 and Time 3. Although text instructions included a 48-hour completion timeframe, completed questionnaires were accepted within 72 hours. Finally, as shown in Fig. 1, randomization was adjusted via Qualtrics to account for the high attrition rates in the break and daily time-cap detox groups, ensuring that each group maintained a similar number of participants.

2.3.1. Insta/TikTok break

Participants were required to deactivate their Instagram and/or TikTok accounts within 24 hours of completing baseline measures. Deactivation of accounts reduced the risk of accessing the app on other devices. All participants were issued with a tip sheet about how to deactivate Instagram and TikTok, types of activities participants could do during the detox (e.g., time with family/friends, journaling, listening to music), and how to reactivate the apps upon detox completion. Participants provided their social media account names upon deactivation in order to facilitate random compliance checks across the 7 days.

2.3.2. Daily time-cap

Participants were required to reduce their social media usage to 30 minutes or less per day within 24 hours of completing baseline measures. This time limit included usage of all photo-based social media apps on iPhones, including Instagram, TikTok, Snapchat, Facebook, YouTube, and Pinterest. Participants were provided with tip sheets about how to set time limits, how to take screen shots of screen time, and how to reduce the risk of going over the time limit (e.g., moving social media apps to a hidden folder).

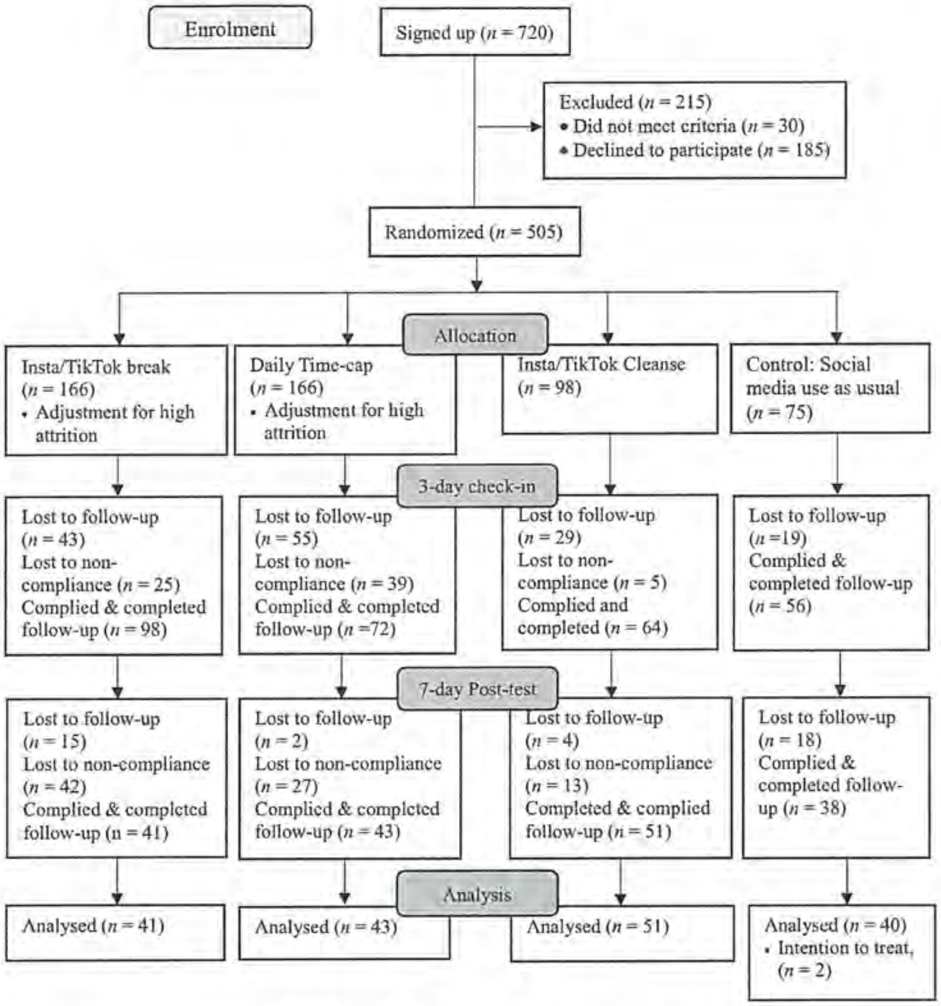

Fig. 1. CONSORT flow chart of participants.

2.3.3. *Insta/TikTok cleanse*

Participants were informed about what constitutes appearance-focused content on TikTok and Instagram (e.g., fitspiration, beauty, fashion, posed bodies) and the types of profiles who are likely to post this type of content (influencers, peers, celebrities). They were then asked to remove 10–15 appearance-focused profiles from each of their Instagram and/or TikTok accounts. Participants were provided with a tip sheet for both Instagram and TikTok about how to unfollow profiles or click 'not interested' on appearance-focused content received in their feeds.

2.4. *Design and data analyses*

All data analyses were conducted using IBM SPSS (version 28). The study employed a mixed model design. The independent variable was social media detox with four levels (Group: Insta/TikTok break, daily time-cap, Insta/TikTok cleanse, or control), and the within group variable was Time with three levels (Baseline, Time 2, Time 3). The five dependent variables were self-objectification, appearance satisfaction, body appreciation, media pressure, and wellbeing. To test the hypotheses, a series of 4 (Group) × 3 (Time) mixed analyses of variance (ANOVAs) were performed to examine the effects of the 7-day social media detox on each of the five dependent variables from baseline to Time 2 and Time 3 and from Time 2 to Time 3. Bonferroni adjustments were included in all main analyses to control for multiple comparisons. Partial eta-squared were calculated as effect sizes for each outcome variable with values of 0.01, 0.06, and 0.14 indicating small, medium, and large effect sizes, respectively (Cohen, 1988). A power analysis (G*power 3.1) indicated that a sample size of 158 participants was considered adequate for a mixed ANOVA design, assuming a power level of $1-\beta = 0.80$, an 80 % confidence level, and a moderate effect size of 0.25.

3. Results

3.1. *Sample characteristics*

At baseline, just over 50 % of participants spent more than 2 hours on social media per day. Instagram was the most used platform daily (45 %), followed by TikTok (34 %), Snapchat (27 %), Facebook (16 %), and other (e.g., Pinterest, YouTube; 7 %). The most viewed/followed content (a few days per week to daily) was friends and family (81 %), followed by comedy (71 %), beauty/fashion (59 %), food/cooking (58 %), current events 55 %, fitness (54 %), vloggers/influencers (49 %), entertainment/celebrity news (48 %), gaming (26 %) and other (11 %). The average BMI was 25.12 (*SD* = 11.78).

3.2. *Preliminary analyses*

A flow chart presented in Fig. 1 shows the progress of completers and non-completers through each phase of the study. Although 720 participants initially signed up to the study, a total of 185 participants

completed measures at each time point. However, 10 participants attempted baseline measures twice, leading to their allocation to more than one condition. Consequently, their data were excluded resulting in a final sample of 175 participants. Missing values in all variables did not exceed 3 %. Missing data analysis followed to examine whether values were missing completely at random. Little's MCAR test (Little, 1988) was not significant, $\chi^2 = 69.81$, $p = .584$, suggesting that values were missing entirely at chance. To control for the impact of attrition bias, we conducted intention-to-treat analyses where missing data were imputed using participants' last observation carried forward (Lachin, 2000). Homogeneity of covariance as indicated by Box's test ($p > .05$) was met for body appreciation, media pressure, and wellbeing. However, appearance satisfaction and self-objectification departed from Box's test assumption and Mauchly's tests of sphericity were violated for all variables ($p < .05$); therefore, Greenhouse-Geisser estimates were reported (Verma, 2015). Equality of error variance-covariance as indicated by Levene's test ($p > 0.05$) was met for all outcomes at each timepoint.

A series of one-way ANOVAs showed that the four conditions did not differ on age, $F(3, 171) = 1.06$, $p = .367$, social media use, $F(3, 171) = 0.87$, $p = .456$ or BMI, $F(3, 170) = 1.87$, $p = .136$. Furthermore, groups did not differ on baseline measures of self-objectification, $F(3, 171) = 3.02$, $p = .824$, appearance satisfaction, $F(3, 171) = 2.53$, $p = .059$, body appreciation, $F(3, 171) = 1.35$, $p = .261$, media pressure, $F(3, 171) = 1.78$, $p = .153$, or wellbeing, $F(3, 171) = 2.41$, $p = .069$. Means and standard deviations for outcomes across time can be seen in Table 1.

3.3. Main analyses

3.3.1. Self-objectification

There was no significant Group × Time interaction, $F(5.33, 303.81) = 1.76$, $p = .117$, $\eta^2_p = .03$ or main effect of Group, $F(3, 171) = .074$, $p = .974$, $\eta^2_p = .001$ on self-objectification. However, as seen in Fig. 2, there was a main effect of Time, $F(1.77, 303.81) = 9.01$, $p < .001$, $\eta^2_p = .05$ whereby, overall, self-objectification decreased from Baseline to Time 3, ($p < .001$) and from Time 2 to Time 3, ($p = .015$).

3.3.2. Appearance satisfaction

There was a significant Group × Time interaction, $F(5.41, 308.60) = 4.03$, $p = .001$, $\eta^2_p = .07$ on appearance satisfaction. As shown in Fig. 3, planned comparisons showed that those assigned to the Insta/TikTok break reported an increase from Baseline to Time 3, $t(81) = 5.56$, $p < .001$. Participants assigned to the daily time-cap group reported increases in appearance satisfaction from Baseline to Time 2, $t(85) = 2.51$, $p = .041$ and Time 3, $t(85) = 5.56$, $p < .001$, but no increases from Time 2 to Time 3, $t(85) = 1.95$, $p = .153$. The Insta/TikTok cleanse group reported increased appearance satisfaction from Baseline to Time 2, $t(101) = 4.44$, $p < .001$, from Baseline to Time 3, $t(101) = 5.56$, $p < .001$, and from Time 2 to Time 3, $t(101) = 2.51$, $p = .041$. No significant increases in appearance satisfaction were found for the control group from Baseline to Time 2 or Time 3. There was no main effect of Group, $F(3, 171) = 2.59$, $p = .055$, $\eta^2_p = .04$, but there was a main effect of Time, $F(1.81, 308.60) = 23.96$, $p < .001$, $\eta^2_p = .12$ whereby, overall, appearance satisfaction increased from Baseline to Time 2, ($p = .005$) and Time 3, ($p < .001$).

3.3.3. Body appreciation

There was no significant Group × Time interaction, $F(5.03, 286.81) = 2.15$, $p = .059$, $\eta^2_p = .04$ or main effect of Group, $F(3, 171) = 0.98$, $p = .402$, $\eta^2_p = .02$ on body appreciation. However, as can be seen in Fig. 4, there was a significant main effect of Time, $F(1.68, 286.81) = 6.02$, $p = .005$, $\eta^2_p = .03$ such that, overall, body appreciation improved from Baseline to Time 3, ($p = .013$).

3.3.4. Media pressure

There was no significant Group × Time interaction, $F(5.76, 328.47)$

Table 1
Means and standard deviations for each group at baseline, Day 3, and Day 7.

Measure	Insta/TikTok Break ($n = 41$)			Daily Time-Cap ($n = 43$)			Insta/TikTok Cleanse ($n = 51$)			Control ($n = 40$)		
	Baseline *M (SD)*	Day 3 *M (SD)*	Day 7 *M (SD)*	Baseline *M (SD)*	Day 3 *M (SD)*	Day 7 *M (SD)*	Baseline *M (SD)*	Day 3 *M (SD)*	Day 7 *M (SD)*	Baseline *M (SD)*	Day 3 *M (SD)*	Day 7 *M (SD)*
Self-objectification	2.88 (0.75)	2.77 (0.79)	2.67 (0.85)	2.91 (0.71)	2.76 (0.76)	2.61 (0.78)	2.84 (0.65)	2.76 (0.83)	2.56 (0.77)	2.76 (0.81)	2.78 (0.77)	2.81 (0.79)
Appearance Satisfaction	2.65 (0.80)	2.74 (0.85)	2.89 (0.91)	2.85 (0.94)	3.07 (0.89)	3.19 (0.84)	2.97 (0.94)	3.24 (0.78)	3.38 (0.81)	3.17 (0.78)	3.16 (0.81)	3.14 (0.76)
Body Appreciation	3.11 (0.83)	3.16 (0.79)	3.30 (0.90)	3.27 (0.76)	3.33 (0.75)	3.40 (0.73)	3.27 (0.91)	3.47 (0.84)	3.54 (0.93)	3.49 (0.89)	3.49 (0.91)	3.42 (0.82)
Media Pressure	3.79 (1.15)	3.63 (1.06)	3.51 (1.17)	3.63 (1.08)	3.30 (1.07)	3.04 (1.11)	3.64 (1.09)	3.50 (1.01)	3.30 (1.02)	3.23 (1.23)	3.05 (1.16)	3.15 (1.19)
Wellbeing	15.34 (5.71)	11.85 (6.01)	13.71 (5.63)	16.53 (5.38)	13.88 (4.45)	18.88 (4.45)	17.96 (5.11)	14.86 (5.57)	14.45 (5.40)	17.93 (5.04)	13.53 (5.26)	13.03 (5.68)

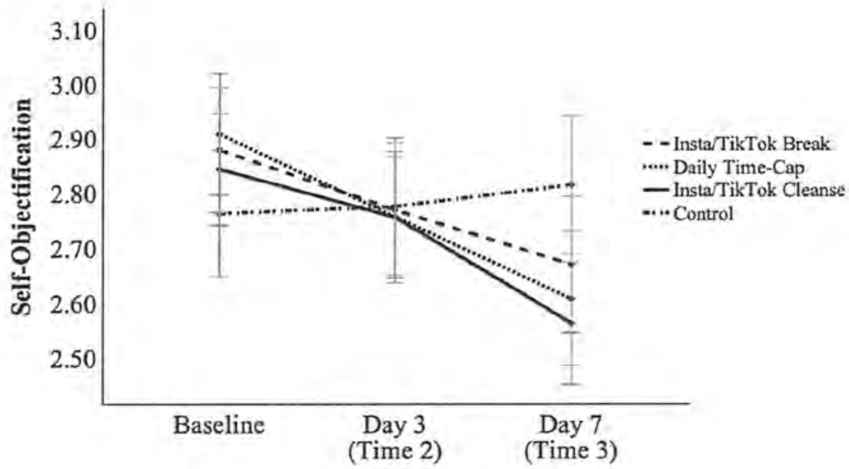

Fig. 2. Changes of self-objectification across 1 week. Note. Scores for self-objectification range from 1 to 5, but the Y axis has been adapted to increase clarity when interpreting the figure. Error bars represent ± 1 standard error.

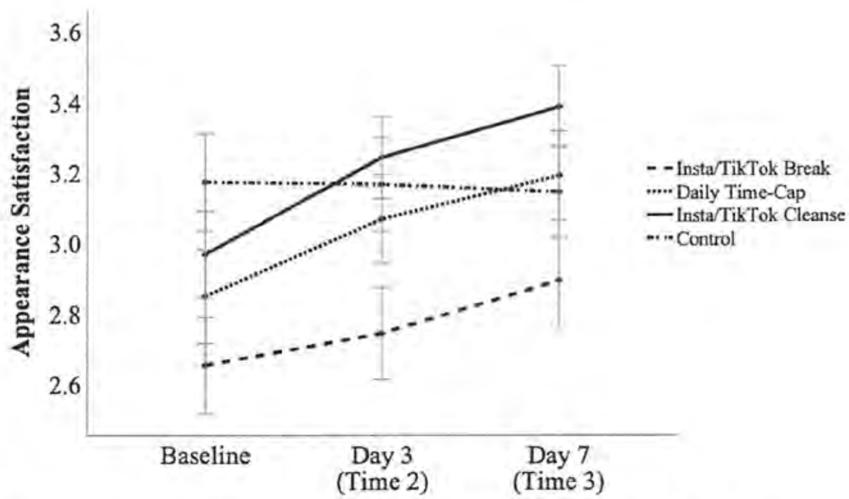

Fig. 3. Changes of appearance satisfaction across 1 week. *Note.* Scores for appearance satisfaction range from 1 to 5, but the Y axis has been adapted to increase clarity when interpreting the figure. Error bars represent ± 1 standard error.

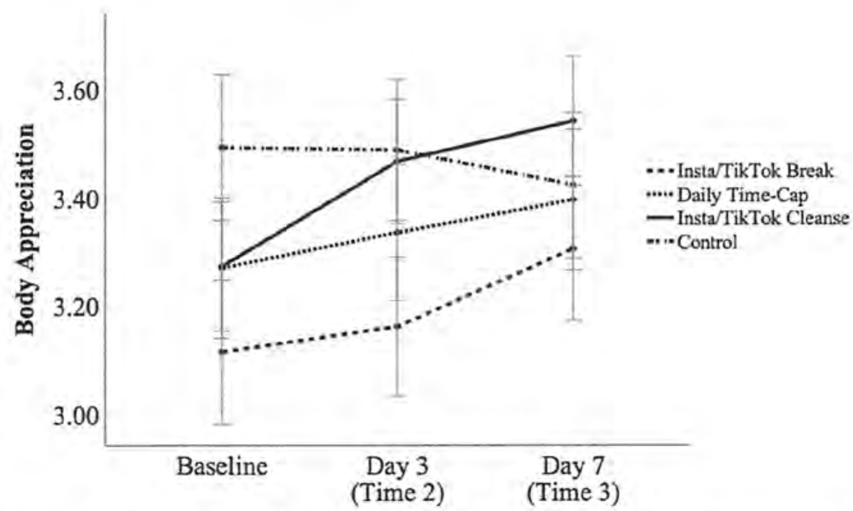

Fig. 4. Changes of body appreciation across 1 week. Note. Scores for body appreciation range from 1 to 5, but the Y axis has been adapted to increase clarity when interpreting the figure. Error bars represent ± 1 standard error.

$= 1.24$, $p = .287$, $\eta_p^2 = .02$ or a main effect of Group, $F(3, 171) = 1.97$, $p = .120$, $\eta_p^2 = .03$ on media pressure. However there was a main effect of Time, $F(1.92, 328.47) = 10.62$, $p < .001$, $\eta_p^2 = .06$ on media pressure (see Fig. 5), such that overall, media pressure decreased from Baseline to Time 2, ($p = .014$) and Time 3, ($p < .001$).

3.3.5. Wellbeing

There was a significant Group × Time interaction, $F(5.20, 296.41) = 13.42$, $p < .001$, $\eta_p^2 = .19$ on wellbeing. As shown in Fig. 6, planned comparisons showed that those assigned to the Insta/TikTok break reported decreased wellbeing from Baseline to Time 2, $t(81) = -4.89$, $p < .001$, with no significant changes from Baseline to Time 3, $t(81) = -2.18$, $p = .091$. However, this group reported an increase in wellbeing from Time 2 to Time 3, $t(81) = 3.54$, $p = .002$. Although those assigned to the daily time-cap reported decreased wellbeing from Baseline to Time 2, $t(85) = -3.81$, $p < .001$, an increase in wellbeing was reported from Baseline to Time 3, $t(85) = 3.21$, $p = .005$, and from Time 2 to Time 3, $t(85) = 9.77$, $p < .001$. In contrast, the Insta/TikTok cleanse group reported decreases in wellbeing from Baseline to Time 2, $t(101) = -4.85$, $p < .001$ and from Baseline to Time 3, $t(101) = -5.23$, $p < .001$, but no significant changes were found from Time 2 to Time 3, $t(101) = -.09$, $p = 1.00$. Finally, the control group reported decreased wellbeing from Baseline to Time 2, $t(81) = -6.09$, $p < .001$, and from Baseline to Time 3, $t(81) = -6.46$, $p < .001$, with no significant change from Time 2 to Time 3, $t(81) = -0.94$, $p = 1.00$. There was a main effect of Group, $F(3, 171) = 2.81$, $p = .041$, $\eta_p^2 = .05$ on wellbeing, such that overall, the groups differed on wellbeing. Results also showed a main effect of Time, $F(1.92, 328.47) = 10.62$, $p < .001$, $\eta_p^2 = .06$ on wellbeing, showing that overall, wellbeing decreased from Baseline to Time 2, ($p < .001$) and increased from Baseline to Time 3, ($p < .001$) and from Time 2 to Time 3 ($p < .001$).

4. Discussion

The objective of this study was to conduct a randomized controlled trial investigating the efficacy of three distinct 7-day social media detox strategies (Insta/TikTok break, daily time-cap, or Insta/TikTok cleanse) relative to social media use as usual (control) on young women's body image and wellbeing. To the authors' knowledge, this study represents the first of its kind to directly compare these varying detox strategies. Overall, findings show that the cleanse condition yielded the most advantageous outcomes for appearance satisfaction (moderate effect size), whereas imposing a daily time limit positively impacted women's wellbeing (large effect size). More specifcally, participants in the Insta/TikTok cleanse and daily time-cap conditions reported increased levels of appearance satisfaction from baseline to day 3 (Time 2) and day 7 (Time 3). Notably, women in the Insta/TikTok cleanse group continued to report increased appearance satisfaction from day 3 to day 7 as a result of cleansing their Instagram and TikTok feeds from appearance-focused content. In terms of wellbeing, women in the daily time-cap group reported increased levels from baseline to day 7. Furthermore, wellbeing increased from day 3 to day 7 for those in the Insta/TikTok break and daily time-cap groups. Interestingly, although the Insta/TikTok break and daily time-cap groups showed overall improvements in wellbeing, all three detox groups (and the control) reported decreased wellbeing from baseline to day 3 suggesting that the initial stages of the study were likely challenging for participants. None of the detox strategies impacted self-objectification, body appreciation, or media pressure. These preliminary findings may provide women with options to effectively facilitate a digital detox aimed at enhancing appearance satisfaction and overall wellbeing.

The positive effect on young women's appearance satisfaction after cleansing their Instagram and TikTok feeds of appearance-focused content for seven days is novel and noteworthy. This finding reinforces earlier qualitative research (Hockin-Boyers et al., 2021), which highlighted how women embarking on weightlifting during eating disorder recovery or those deemed 'at risk' of such disorders, articulated the significance of recognizing triggering content and the empowering effect of actively disengaging from it on social media. Moreover, it advances existing literature by demonstrating that this adaptive skill is not exclusive to individuals susceptible to eating disorders. In other words, this flexible capability extends to young women who perceive the influx of appearance-focused content on their Instagram and TikTok feeds as detrimental to their self-image, irrespective of their risk status. Particularly noteworthy is that although appearance satisfaction increased from baseline to day 7 for the Insta/TikTok break and daily time-cap groups, continued increase in appearance satisfaction from day 3 to day 7 was found only for the Insta/TikTok cleanse group. This finding supports prior qualitative research which indicated that the skill of cleansing one's feed (or digital pruning) is a "long-term effort of investment" (Hockin-Boyers et al., 2021). It is therefore plausible that the more often young women engage in the act of cleansing their Instagram and TikTok feed of appearance-focused content, the more impactful this strategy could be on their appearance satisfaction.

In parallel with the cleanse group, reducing time on social media was impactful on appearance satisfaction within three days of that detox

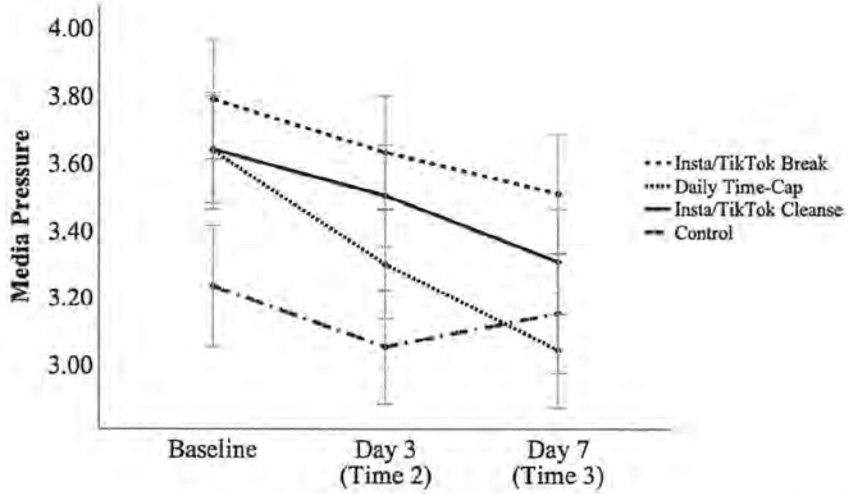

Fig. 5. Changes of media pressure across 1 week. *Note.* Scores for media pressure range from 1 to 5, but the Y axis has been adapted to increase clarity when interpreting the figure. Error bars represent ± 1 standard error.

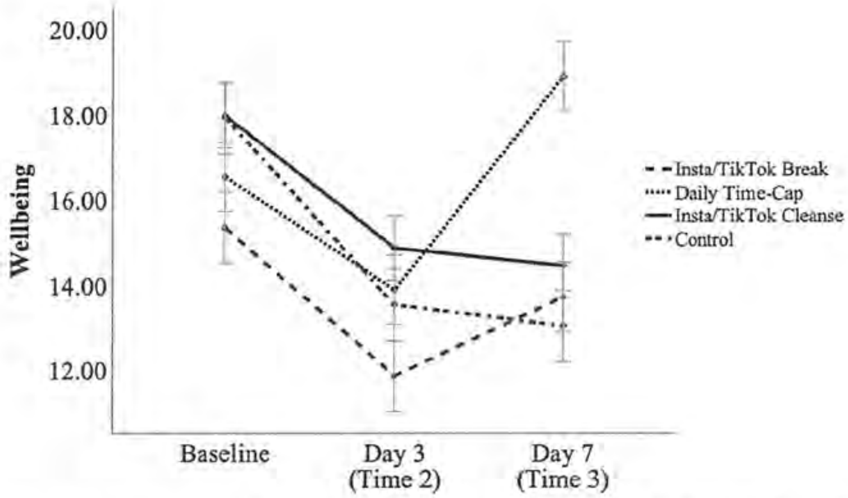

Fig. 6. Changes of wellbeing across 1 week. Note. Summed scores for wellbeing range from 0 to 25, but the Y axis has been adapted to increase clarity when interpreting the figure. Error bars represent ± 1 standard error.

strategy, whereas abstinence (Insta/TikTok break) did not yield similar results. Perhaps actively curating Instagram and TikTok feeds to filter out potentially detrimental appearance-centric content or implementing restricted time limits on photo-based social media platforms, yields greater benefits during the initial stages of a detox in terms of enhancing appearance satisfaction, compared to sudden disengagement from these platforms. It is also possible that the restricted time spent on photo-based social media platforms prompts young women to be more discerning with their usage, avoiding aimless scrolling through feeds inundated with idealized imagery. Interestingly, although our findings resonate with previous research (e.g., Smith et al., 2024; Thai et al., 2021), they also offer nuanced insights into the distinctions and challenges between complete abstinence and reduced usage of appearance-focused apps. For instance, Smith et al. (2024) showed that a meaningful 7-day break from social media, where young women either abstained entirely or limited their daily usage to an average of 14 minutes, positively impacted body satisfaction. However, their study also revealed that complete abstinence was often impractical and challenging for many participants. That finding is reinforced by the high attrition rates observed in our study for both the abstinence and time-capped detox groups, suggesting that time away from image-based apps may be difficult to sustain. Nevertheless, our findings indicate that reducing time on these apps could serve as a more feasible initial step toward a digital detox than complete abstinence.

To our knowledge, this is the first study to directly compare three types of 7-day detox strategies on young women's wellbeing and the findings are clear. Despite an initial decline in young women's wellbeing during the first three days of the digital detoxes, adherence to a 30-minute daily time limit on photo-based apps showed a positive and sustained effect. Similarly, wellbeing improved from day 3 to day 7 for women who abstained altogether from Instagram and TikTok use. Conversely, across the week of the study, wellbeing declined for the control group. Our findings align with previous research indicating that imposing daily limits of 10–30 minutes over 1–2 weeks on photo-based and other social media platforms leads to increased perceived wellbeing (Coyne & Woodruff, 2023) and other aspects of wellbeing such as reduced loneliness (Hunt et al., 2018). They also contribute to those past studies by showing that, although the first three days are likely to be the most challenging, increased duration of restricted time or abstinence strategies are likely to enhance wellbeing.

Unexpectedly, and unlike the Insta/TikTok break and daily time-cap groups, the Insta/TikTok cleanse group did not report a bounce back from the initial dip in wellbeing at day 3, and instead their wellbeing remained at the same level from day 3 to day 7. There are a few possibilities for these outcomes. First, implementing a daily time restriction for social media usage could prompt young women to reflect on their priorities (e.g., connecting with friends, viewing content of interest) while engaging with these platforms. As discussed earlier, this initiative may reduce idle scrolling and minimize exposure to harmful content, ultimately enhancing wellbeing. In contrast, cleansing appearance-focused content from Instagram and TikTok entails dedicating time to reviewing content and evaluating any potential negative effects. Although cleansing may enhance appearance satisfaction, the time invested in this process could inadvertently expose women to content that could impact their wellbeing. Alternatively, the focus on removing appearance-related content, a relatively novel approach for participants, may have prompted them to recognize the extent to which they were consuming such content, potentially affecting their overall wellbeing. Interestingly, while there was an overall reduction in wellbeing, it was only in the first three days of study involvement, as wellbeing did not significantly decrease from day 3 to day 7. This finding suggests that future research could investigate wellbeing over longer periods for adjustment to the cleansing practice. Given current findings, it would also be interesting to know whether a combination of cleansing and daily time restrictions on photo-based platforms could enhance both appearance satisfaction and wellbeing.

Contrary to our expectations, we found no improvements over time for any specific detox approaches regarding self-objectification, media pressure, or body appreciation. Our results diverged from those of Roberts et al. (2022), who found that pre- and early adolescent female dancers reported lower self-objectification following a 3-day abstinence from social media. Considering the age diversity within the sample groups and in accord with objectification theory (Fredrickson & Roberts, 1997), it is plausible that self-objectification becomes more deeply ingrained during young adulthood compared to pre- or early-adolescence. Consequently, it may be less amenable to change during this developmental stage, particularly given the brief detox period of seven days. Similarly, the depth of internalized media pressure during young adulthood might hinder its responsiveness to change within a short intervention window. In fact, despite young women reporting improved appearance satisfaction through the removal of potentially triggering appearance content from Instagram and TikTok feeds, it is important to acknowledge that media pressure to maintain societal appearance standards remained pervasive and unyielding.

Given that lower body appreciation is linked with higher Instagram use (Duan et al., 2022), and negatively affected by exposure to attractive

celebrity images on social media (Brown & Tiggemann, 2020), it was surprising to find that removing appearance-focused content from Instagram and TikTok, abstaining from these apps, or limiting time on photo-based apps did not enhance body appreciation. This finding raises the possibility that fostering a positive attitude towards one's body may necessitate exposure to content that promotes body positivity. However, a recent study demonstrated that passive viewing of body positive content on popular Facebook accounts over a 14-day period failed to influence women's body appreciation (Fardouly et al., 2023). Notably, both the present study and that of Fardouly et al. (2023) shared a commonality in their use of trait measures to explore potential cumulative impacts on body appreciation. To enhance future investigations, researchers might consider evaluating body appreciation through state measures or incorporating *active* engagement with body positivity influencers.

4.1. Implications

Current findings offer significant implications for addressing appearance dissatisfaction and low wellbeing in young women. Recognizing the considerable challenges many young women face in abstaining from social media apps for an entire week, our research underscores the availability and appeal of multiple detox strategies. Notably, we offer preliminary evidence supporting the efficacy of cleansing one's social media feed from appearance-focused content in enhancing appearance satisfaction. Whether by temporarily reducing time spent on social media or abstaining from it altogether, young women overwhelmed by content or experiencing diminished wellbeing have accessible and cost-effective detox options to consider and implement. Indeed, findings suggest that digital detox strategies may be viewed as part of a broader suite of digital interventions (see Mahon & Seekis, 2022) aimed at improving body image in young women. Ultimately, our findings could inform policy recommendations structured to foster the adoption of healthy digital practices. For instance, policymakers could consider incentivizing social media platforms to introduce features designed to encourage positive content consumption behaviors.

4.2. Limitations and future directions

Current findings should be interpreted within the context of several limitations. First, the three detox strategies were conducted for a period of seven days with no follow-up measures, therefore, longer-term effects on appearance satisfaction and wellbeing remain unknown. Replication studies with larger sample sizes and longer time frames are necessary to help establish effect size benchmarks and provide further insight into the cumulative nature of digital detox strategies. Second, time spent on other photo-based apps (e.g., Snapchat) in lieu of deactivating or during the cleanse of appearance-focused content from Instagram and TikTok may have increased, potentially influencing the outcomes for these groups. Future research could seek to include reporting of time spent on other apps during the intervention period. It is also reasonable to infer that participants continued to engage in appearance-related interactions online or offline, potentially influencing the findings. Future research could examine whether detox strategies help individuals manage these activities in a positive way or if positive appearance-focused interactions shape their approach to social media detoxing.

Third, despite the improvements in body satisfaction observed during and after the 7-day cleanse, the short timeframe may have allowed the algorithm to continue promoting appearance-related content. Future research could explore whether participants noticed any changes in the type of content appearing on their feed after a brief cleanse. Additionally, asking participants to remove appearance-focused content from their Instagram and TikTok feeds likely led to the removal of body-positive content. Future studies could investigate whether differences in body satisfaction arise between cleansing the feed of all appearance-focused content versus only idealized content.

Fourth, although we requested participants send screen shots of daily time limits and randomly checked deactivation of Instagram and TikTok accounts, we did not objectively assess adherence via trackers to mitigate privacy issues. Indeed, this process likely contributed to the high attrition rates for the abstinence and time-capped detox approaches. Similarly, while self-report measures were used to determine adherence to cleansing Instagram and TikTok of potentially harmful appearance content, future research could usefully include an app to monitor adherence checks. However, it is crucial to acknowledge that potential apprehensions regarding data breaches might deter participants from willingly downloading such applications onto their devices. Fifth, we did not assess mechanisms underlying the effect of cleansing on appearance satisfaction or applying daily time limits on wellbeing. Women who engaged in these strategies may have experienced a heightened sense of agency by actively taking control over the content they consumed. It would therefore be interesting to examine whether a sense of agency underlies these effects. Finally, the homogenous sample, comprising mostly White female undergraduates, limits generalizability. Future research could seek to investigate these detox strategies in more diverse samples in terms of culture, gender, age, and sexual orientation.

4.3. Conclusion

This study sheds light on the varying effects of three social media detox strategies for promoting appearance satisfaction and overall wellbeing. Our findings demonstrate that while complete abstinence from social media may not be feasible for everyone, alternative detox strategies such as cleansing one's social media feed or reducing usage time can yield tangible benefits. Notably, the active curation of content to filter out potentially triggering appearance-focused material emerged as a particularly promising approach, offering a viable pathway to enhancing appearance satisfaction without the need for complete disengagement from digital platforms. By providing young women with cost-effective ways to navigate social media apps mindfully, we can empower them to cultivate healthier relationships with technology and enhance their appearance satisfaction and wellbeing.

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CRediT authorship contribution statement

Veya Seekis: Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Kate E Mulgrew:** Writing – review & editing, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Ivanka Prichard:** Writing – review & editing, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Hannah Manning:** Writing – review & editing, Resources, Project administration, Methodology, Investigation, Data curation, Conceptualization. **Isabella Wood:** Writing – review & editing, Resources, Project administration, Methodology, Investigation, Data curation, Conceptualization. **Cloudia Stevenson:** Writing – review & editing, Resources, Project administration, Methodology, Investigation, Data curation, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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The mediating role of anxiety and depression between problematic social media use and bulimia nervosa among Lebanese university students

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Abstract

Background Bulimia nervosa (BN) is a disorder that is characterized by binge eating and inappropriate compensatory behavior to control weight. The aim of this study was to evaluate the mediating role of anxiety and depression between problematic social media use (PSMU) and BN among a sample of Lebanese university students.

Methods This cross-sectional study was carried out between July and September 2021; a total of 363 university students was recruited through convenience sampling. The PROCESS SPSS Macro version 3.4, model four was used to test the indirect effect and calculate three pathways. Pathway A determined the regression coefficient for the effect of PSMU on mental health issues (depression/anxiety); Pathway B examined the association between mental health issues on BN, and Pathway C' estimated the direct effect of PSMU on BN. Pathway AB was used to calculate the indirect effect of PSMU on BN via depression/anxiety.

Results Results showed that depression and anxiety partially mediated the association between PSMU and BN. Higher levels of PSMU were associated with more depression and anxiety; higher depression and anxiety were associated with more BN. PSMU was directly and significantly associated with more BN. When entering anxiety (M1) then depression (M2) as consecutive mediators in a first model, the results showed that only depression mediated the association between PSMU and bulimia. When taking depression (M1) then anxiety (M2) as consecutive mediators in a second model, the results showed that the mediation PSMU → Depression → Anxiety → Bulimia was significant. Higher PSMU was significantly associated with more depression, which was significantly associated with more anxiety, which was significantly associated with more bulimia. Finally, higher PSMU was directly and significantly associated with more bulimia

Conclusion The current paper highlights the relationship that social media use has on BN and other aspects of mental health such as anxiety and depression in Lebanon. Future studies should replicate the mediation analysis conducted in the current study while taking into account other eating disorders. Additional investigations of BN and

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its correlates must strive to improve the comprehension of these associations' pathways through designs that allow to draw temporal frameworks, in order to efficiently treat this eating disorder and prevent its negative outcomes.

Plain English summary

Bulimia nervosa, an eating disorder, is characterized by an impulsive consumption of food in a short period of time, followed by behaviors that compensate the eating such as vomiting or excessive exercise in order to avoid weight gain. Individuals with problematic social media use were found to have higher levels of bulimia symptoms. Symptoms of bulimia can also be associated with both depression and anxiety. The aim of the current study was to examine the mediating role of anxiety and depression between problematic social media use and bulimia nervosa. The results of our study found that problematic social media use was directly associated with more bulimia nervosa and also associated with higher depression and anxiety, both of which were associated with bulimia nervosa. Tackling associated disorders may help reduce symptoms of bulimia nervosa. Clinicians should carefully examine these associations while assessing and implementing treatment plans.

Keywords Bulimia nervosa, Anxiety, Depression, Problematic social media use, Lebanon

Introduction

The most severe mental illnesses affecting adolescents and young adults today are eating disorders (EDs), such as anorexia nervosa (AN), bulimia nervosa (BN), and binge eating disorder (BED) [1]. Worldwide, both males and females of all ages exhibit BN, which is linked to increased mortality risk [2]. BN is defined as "recurrent binge eating episodes along with inappropriate compensatory behaviors, and is linked to serious medical problems, mental comorbidity, and psychosocial impairment" [3]. People with BN may exhibit bursts of impulsive consumption of a lot of food in a short amount of time, followed by compensatory behaviors (such as excessive exercise, vomiting, laxative abuse, limited food intake) to prevent weight gain [4, 5]. In the systematic review of Galmiche et al., the lifetime prevalence rates of BN ranged from 0.1% to 1.3% in men and from 0.3% to 4.6% in women [6]. The peak age of incidence of BN ranged between 15 and 29 years [2]. In addition, compared to persons without an ED, all participants with EDs had greater median incomes and lower education [7]. A prior study conducted on EDs in Lebanon found that BN was the most prevalent ED (46.1%) ,followed by anorexia nervosa (39.4%) and binge eating (14.4%) [1]. Additionally, prior research revealed that 11.4% of university students in Lebanon had AN, BN, or BED diagnosis and that 21.2% were at risk for developing an ED [8]. ED behaviors are thought to be painful, as people are often engaged in extreme measures to alter body shape and abate concern about the body [9].

Body dissatisfaction is often used as a term to describe the body-related negative self-evaluation of an individual [10]. Body dissatisfaction was a strong prospective predictor of the severity of suicidal thoughts, and BN symptoms (binge eating and purging) predicted suicidal ideation [9]. When attempting to understand the emergence of body dissatisfaction and EDs, culture is a crucial factor to take into account since it determines the environment in which attitudes regarding the body are formed [11]. Lebanese media, similar to Western cultures, promotes the culture of "thinness" and "perfection" [12]. Lebanese are more susceptible to media messages encouraging them to eat less and exercise more in order to lose weight or gain muscle mass [13–18]. They also fear social criticism and are more susceptible to peer opinions. In addition, compared to their Cypriot peers, Lebanese women are more self-conscious about their body size [13].

EDs are multi-factorial and include biological, psychological, intrapersonal, and environmental influences. Exposure to media, one environmental factor, has been linked to the emergence of these problems and is probably mediated by thin-ideal internalization [19]. According to the biopsychosocial model, problematic social media use (PMSU) is characterized by the presence of addiction-like symptoms such as mood modifications (i.e., alterations in mood states with the excessive social media use), tolerance (i.e., an increase in the amount of time spent on social media), withdrawal symptoms (i.e., feeling contradicted or irritable when restricted from using social media), conflict (i.e., relationship problems as a result from using social media) and relapse (i.e., going back to social media use after stopping for a while) [20, 21]. Scales to assess Social Media Use as a type of addiction include several criteria of behavioral addictions such as: preoccupation, tolerance, withdrawal, persistence, displacement, problem, deception, escape and conflict [22, 23]. A previous research found a significant positive correlation between BN and the time spent on social networking

sites [24]. Furthermore, in two recent meta-analyses, Hinojo-Lucena and colleagues found that those with problematic use of internet had significantly higher rates of both EDs (AN, BN, and BED) and ED-related symptoms (food obsession, loss of control eating, and dieting) [25]. While aiming to examine an association between social media use and eating concerns, a study found a strong association between the two [19]. Social media is more widely available at young age; just one click can set off a range of ideas and behaviors that mimic EDs in those people, to conform to what society considers to be attractive [19]. With that being said, the pressure of media influence was associated with more EDs (restrained and emotional eating) among Lebanese undergraduates [26].

While many factors contribute to the development of BN, having a comorbid disorder can be associated with more severe symptoms of EDs [27, 28]. Godart and colleagues (2000) found that anxiety disorders were frequently present before the occurrence of EDs [29]. The results of a previous study suggested that the comorbidity of an ED with anxiety and depression was high [30]. An earlier network analysis study revealed that the anxiety symptoms of shakiness, unsteadiness, and dizziness were very central and closely related to the BN symptoms in the anxiety and BN network. Similarly, in the depression and BN network, the lack of interest in sex and changes in appetite were highly central [31]. Therefore, by identifying the core symptoms of the comorbid disorders (e.g., comorbid anxiety and depression symptoms), treatment of BN could be improved to concentrate on these symptoms. Anxiety positively contributed to addictive social networking, with social media use shown to be positively associated with depression among young adults [32, 33]. Depressive symptoms were also found to predict eating behaviors ten years later [34, 35]. A descriptive review found that the levels of neurocognitive alterations and impairment in individuals with AN were proportional to the severity of depressive symptoms [36]. It is noteworthy to also mention that depression can be secondary to EDs according to the results of a longitudinal study [37]. Similarly, anxiety moderated the association between body dissatisfaction and restrained eating; when levels of anxiety are high, body image dissatisfaction was more strongly associated with restrained eating [35]. Furthermore, depression moderated the association between body dissatisfaction and orthorexia nervosa [38].

As EDs are very uncommon in the general population, help seeking is frequently avoided or put off for many reasons, such as denial (especially in the case of AN) or stigma and shame (especially in the case of BN) [2]. Most of the epidemiological research on EDs has been conducted in Western nations. There is evidence to support the idea that non-Western nations are not immune to EDs where EDs are spreading, especially in the Middle East [1]. Mental health issues are frequently underestimated in developing countries, although they were shown to be prevalent in Lebanon following the COVID-19 pandemic [39], particularly in the context of a severe socio-economic crisis and political instability [40, 41]. Moreover, Arab cultures and mentalities favor and work hard for a thin and toned body, which puts a lot of pressure on people, therefore, emphasizing the importance of studying BN in these populations. In fact, the sociocultural changes in the Arab countries have led to a shift from the admiration of curvy bodies to thin ones, a goal achieved by following ED behaviors [35, 42]. In view of the lack of previous studies that assess the correlates of BN in Lebanon, the aim of this study was to evaluate the mediating effect of anxiety and depression between PSMU and BN in a sample of Lebanese university students. We hypothesize that depression and anxiety may mediate the association between BN and PSMU, where an increase level of PSMU would be associated with higher levels of depression and anxiety, which would be associated with higher BN.

Methods

Study design and participants

This cross-sectional study was carried out between July and September 2021. A total of 363 university students was recruited through convenience sampling from several universities in Lebanon's governorates. Involved people were encouraged to visit a website that would guide them to the consent form, information form (purpose of the current study, anonymity, voluntariness of consent to research), and questionnaire. The data was collected online using the snowball technique in order to reach the target number. All participants responded willingly to the survey. There were no fees for participating in the study. All university students over the age of 18 were eligible to participate. Excluded were only those who refused to complete the survey and those who were not university students; no other exclusion criteria were applied [43].

Minimal sample size calculation

According to the G-power, a minimum of 316 students was deemed necessary to have enough statistical power, based on a 5% risk of error, 80% power, $f^2 = 2.5\%$ and 10 factors to be entered in the multivariable analysis.

Questionnaire and variables

The Arabic self-administered questionnaire with closed-ended questions was anonymous; the questionnaire required approximately 20 minutes to be completed. The questionnaire consisted of different sections. The first

part clarified socio-demographic characteristics: age, sex, marital status, and household crowding index. The latter, reflecting the socioeconomic status of the family, was calculated by dividing the number of persons in the house by the number of rooms in the house excluding the bathrooms and kitchen [44]. The physical activity index was calculated by multiplying the intensity by the frequency by the time of physical activity [45].

The second part of the questionnaire included the following scales:

Eating attitude test (EAT-26)

The EAT, validated in Lebanon in Arabic [46, 47], was used to assess disordered food attitude. The questionnaire comprises twenty-six questions each with six response options, varying from infrequently/almost never/never (0) to always [3]. It is divided into three subscales: dieting (avoidance of fatty foods and preoccupation with thinness), bulimia and food preoccupation, and oral control (self-control over food and social pressure to gain weight). The total score was calculated by summing all questions answers and can vary from 0 to 78. A score of 20 or above indicates possible disordered food attitudes. In this study, only the bulimia subscale was used. The bulimia scale included items such as: "I vomit after I have eaten". The Cronbach's alpha in this study was 0.87.

Body dissatisfaction subscale of the eating disorder inventory-second version (EDI-2)

The body dissatisfaction subscale evaluates the degree of dissatisfaction to the overall body, and to particular body element. It is made of nine items (i.e., "I am satisfied with the shape of my body"), scored on a 4-point Likert scale, from never (0) to always [3]. Higher scores correspond to a higher level of body dissatisfaction [48]. The Arabic version of the scale was used in a previous study [49]. The Cronbach's alpha in this study was 0.60.

Social media disorder scale (SMD)

Validated in Lebanon in Arabic [50], the short form of the SMD was used in this study. It is composed of 9 items (i.e. "Over the last year, have you often felt bad when you when you could not use social media?"), with higher scores reflecting more problematic social media use [22]. The Cronbach's alpha in this study was 0.79.

Lebanese anxiety scale (LAS-10)

Lebanese Anxiety Scale (LAS-10) is a 10-item instrument in Arabic measuring the severity of anxiety symptoms among Lebanese adults [49] and adolescents [50]. This scale was previously used in Lebanon [51, 40]. In LAS-10, the first seven questions are graded from 1 to 10, and the last three questions are graded from 1 to 4 based on the repetitive manifestation of symptoms (i.e., "I feel that the difficulties are accumulating to the point where I can't get through them"). Higher scores indicate higher anxiety levels. The Cronbach's alpha in this study was 0.89.

Patient health questionnaire (PHQ-9)

The PHQ-9 is a 9-item self-report scale (i.e. "Over the past two weeks, how often have you been bothered by the following: little interest or pleasure in doing things"), previously validated in Lebanon in Arabic [52], which is used to assess and check the severity of depression. PHQ-9 total score ranges from 0 to 27, with a cut-off point of 0–4 indicates no depressive symptoms, 5–9 mild depressive symptoms, 10–14 moderate depressive symptoms, 15–19 moderately-severe depressive symptoms, and 20–27 severe depressive symptoms [53]. The Cronbach's alpha in this study was 0.90.

Statistical analysis

SPSS software version 25 was used to conduct data analysis. The normality of the BN score was verified via the skewness and kurtosis values varying between -1 and +1 [54]. A bivariate analysis using the Pearson correlation test served to assess the relationship between the BN score and other continuous variables, whereas the Student t test was used to compare two means. A linear regression was conducted taking the BN score as the dependent variable. The PROCESS SPSS Macro version 3.4, model four [42] was used to test the indirect effect and calculate three pathways. Pathway A determined the regression coefficient for the effect of PSMU on mental health issues (depression/anxiety); Pathway B examined the association between mental health issues on BN, and Pathway C' estimated the direct effect of PSMU on BN. Pathway AB was used to calculate the indirect effect of PSMU on BN via depression/anxiety. A serial mediation analysis was conducted afterwards to test the mediating effect of depression and anxiety consecutively in one model. An indirect effect was deemed significant if the bootstrapped 95% confidence intervals of the indirect pathway AB did not pass by zero [42]. The linear regression and moderation analysis were adjusted over all variables that showed a $p<0.25$ in the bivariate analysis. Significance was defined at $p<0.05$.

Results

Sociodemographic and other characteristics of the participants

A total of 363 students participated in this study; their mean age was 22.65 ± 3.48 years (min = 18; max = 37), with 61.7% females. The mean BN score was 3.10 ± 4.29. Other characteristics are summarized in Table 1.

Table 1 Sociodemographic and other characteristics of the participants (N = 363)

Variable	N (%)
Sex	
Male	139 (38.3%)
Female	224 (61.7%)
Marital status	
Single	343 (94.5%)
Married	20 (5.5%)
	Mean ± SD
Age (in years)	22.65 ± 3.48
Body mass index (kg/m^2)	23.62 ± 4.13
Physical activity index	27.94 ± 20.44
Household crowding index (person/room)	1.01 ± 0.53

SD = Standard Deviation

Moreover, 122 (33.6%) of the participants had eating disorders (EAT scores of 20 or more).

Bivariate analysis

The bivariate analysis results are summarized in Tables 2 and 3. Older age (r = − 0.11) was significantly associated with less BN, whereas higher PSMU (r = 0.31), higher body dissatisfaction (r = 0.16), higher anxiety (r = 0.48)

Table 2 Bivariate analysis of the categorical variables associated with bulimia.

Variable	Bulimia			
	Mean ± SD	***p***	**Effect size**	**Statistical test used**
Sex		0.223	0.130	Student t test
Male	2.76 ± 3.92			
Female	3.31 ± 4.50			
Marital status		0.833	0.052	Student t test
Single	3.11 ± 4.32			
Married	2.90 ± 3.71			

Numbers refer to mean ± SD

Table 4 Multivariable analysis: Linear regression (using the ENTER model) taking bulimia as the dependent variable.

	Beta	β	*p*	95% CI
Age	0.01	0.01	0.867	−0.10; 0.12
Body Mass Index	−0.03	−0.03	0.536	−0.14; 0.07
Physical activity index	0.01	0.05	0.246	−0.01; 0.03
Body dissatisfaction	0.18	0.32	**< 0.001**	0.12; 0.24
Problematic Social media use	0.26	0.14	**0.002**	0.10; 0.43
Anxiety	0.16	0.31	**< 0.001**	0.10; 0.23
Depression	−0.01	−0.02	0.754	−0.10; 0.07

*Reference group; Beta = unstandardized beta; β = standardized beta; CI = Confidence interval; numbers in bold indicate significant *p*-values. Nagelkerke R^2 = .337

and higher depression (r = 0.36) were significantly associated with more BN.

Multivariable analysis

A linear regression taking BN as the dependent variable, showed that higher PSMU (Beta = .26), higher anxiety (Beta = .16) and higher body dissatisfaction (Beta = .18) were significantly associated with more BN (Table 4).

Mediation analysis

The results of the mediation analysis (adjusted over age, sex, BMI, physical activity, body dissatisfaction) showed that depression and anxiety partially mediated the association between problematic social media use and BN (Table 5). Higher problematic social media use was significantly associated with more depression/anxiety, whereas more depression/anxiety was significantly associated with more BN. Finally, higher problematic social media use was directly and significantly associated with more BN (Figs. 1 and 2).

Table 3 Correlation matrix of continuous variables.

	1	2	3	4	5	6	7	8	9
1. Bulimia	1								
2. Age	−0.11*	1							
3. Body Mass Index	0.07	0.29***	1						
4. Physical activity index	0.07	−0.13*	−0.08	1					
5. Household crowding index	0.02	−0.12*	0.02	0.02	1				
6. Problematic Social media use	0.31***	−0.18***	−0.06	0.001	0.07	1			
7. Body dissatisfaction	0.16**	0.08	0.07	0.03	0.01	0.17**	1		
8. Anxiety	0.48***	−0.19***	−0.05	0.10	0.06	0.32***	0.13*	1	
9. Depression	0.36**	−0.16**	−0.02	0.03	0.12*	0.32***	−0.07	0.69***	1

**p* <.05; ***p* <.01; ****p* <.001; numbers refer to Pearson correlation coefficients.

Table 5 Mediation analyses results, taking problematic social media use as the independent variable, depression/anxiety as the mediators and bulimia as the dependent variable

Mediator	Direct effect			Indirect effect		
	Beta	SE	*P*	Beta	Boot SE	Boot CI
Depression	0.34	0.09	<0.001	0.18	0.05	0.10; 0.29*
Anxiety	0.32	0.09	<0.001	0.21	0.05	0.13; 0.31*

*Indicates significant mediation

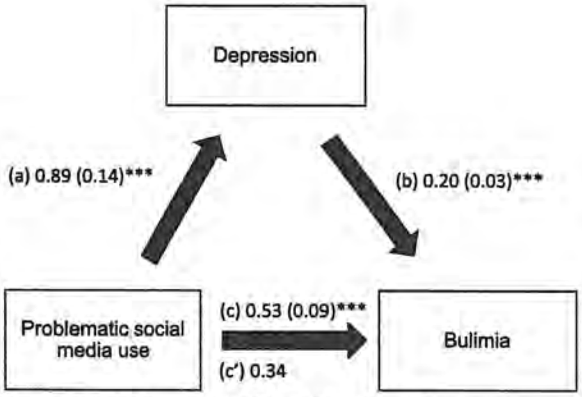

Fig. 1 **a** Relation between problematic social media use and depression (R2 = .133); **b** Relation between depression and BN (R2 = .209); **c** Total effect of problematic social media use and BN (R2 = .130); **c'** Direct effect of problematic social media use and BN. Numbers are displayed as regression coefficients (standard error). ***$p < 0.001$

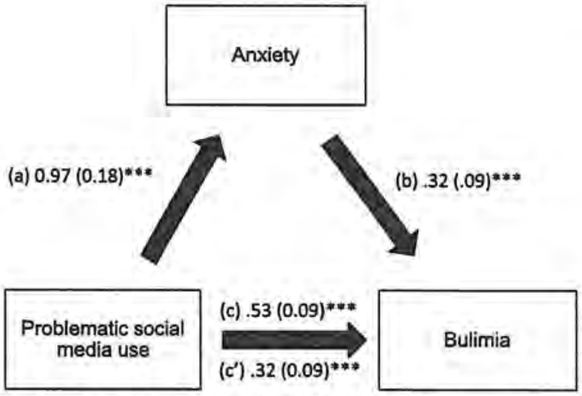

Fig. 2 **a** Relation between problematic social media use and anxiety (R2 = .132); **b** Relation between anxiety and BN (R2 = .279); **c** Total effect of problematic social media use and BN (R2 = .130); **c'** Direct effect of problematic social media use and BN. Numbers are displayed as regression coefficients (standard error). **$p < 0.01$; ***$p < 0.001$

Serial mediation

The mediation analyses were conducted following the indirect effect key below:

Indirect effect 1: PSMU → Depression → Bulimia
Indirect effect 2: PSMU → Anxiety → Bulimia
Indirect effect 3: PSMU → Depression → Anxiety → Bulimia

The results of the mediation analysis (adjusted over age, sex, BMI, physical activity, body dissatisfaction) showed that depression and anxiety mediated the association between problematic social media use and BN (Table 6). When entering anxiety (M1) then depression (M2) as consecutive mediators in Model 1, the results showed that only depression mediated the association between PSMU and bulimia. When taking depression (M1) then anxiety (M2) as consecutive mediators, the results showed that the mediation PSMU → Depression → Anxiety → Bulimia was significant. Higher PSMU was significantly associated with more depression, which was significantly associated with more anxiety, which was significantly associated with more bulimia. Finally, higher PSMU was directly and significantly associated with more bulimia (Fig. 3).

Discussion

The aim of the current study was to examine the mediating role of depression and anxiety between PSMU and BN among a sample of Lebanese university students. Higher levels of PSMU, anxiety and body dissatisfaction were all correlated with BN. Depression and anxiety partially mediated the association between problematic social media use and BN. When entering anxiety then depression as consecutive mediators, the results showed that only depression mediated the association between PSMU and bulimia. When taking depression then anxiety as consecutive mediators, the results showed that the mediation PSMU → Depression → Anxiety → Bulimia was significant.

PSMU, depression and anxiety

In a study conducted on 456 Lebanese residents, 107 (23.7%) were classified as having a social media use disorder [55]. The time spent on smartphone screens increased during the COVID-19 pandemic and lockdowns [56] and was associated with more insomnia [57]. The fear of

Table 6 Indirect effect analyses results, taking problematic social media use as the independent variable, depression and anxiety as consecutive mediators and bulimia as the dependent variable

	Direct effect			Indirect effect		
	Beta	SE	p	Beta	Boot SE	Boot CI
Model 1: anxiety then depression as consecutive mediators.						
Total	0.31	0.09	<0.001	0.22	0.05	0.13; 0.33*
Indirect effect 1				0.20	0.05	0.10; 0.31*
Indirect effect 2				0.01	0.02	−0.03; 0.07
Indirect effect 3				0.01	0.03	−0.04; 0.07
Model 2: depression then anxiety as consecutive mediators						
Total	0.31	0.09	<0.001	0.22	0.05	0.13; 0.33*
Indirect effect 1				0.02	0.05	−0.07; 0.13
Indirect effect 2				0.04	0.04	−0.03; 0.12
Indirect effect 3				0.16	0.04	0.09; 0.25*

*Indicates significant mediation.

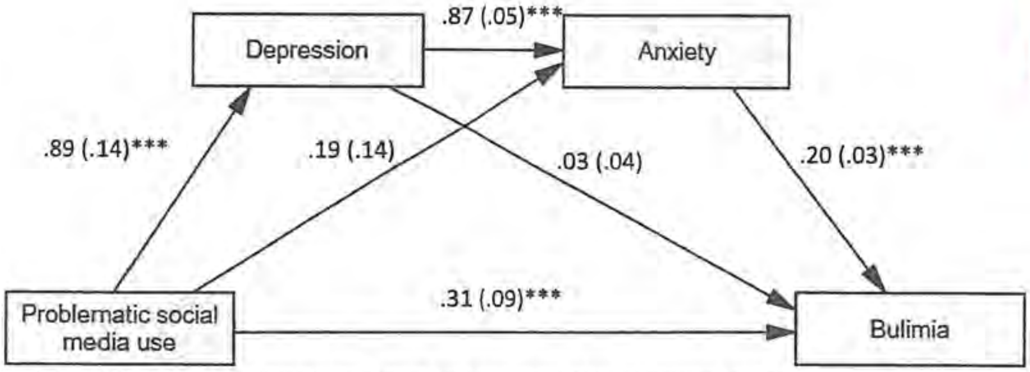

Fig. 3 Serial mediation of the effect of problematic social media use on bulimia, taking depression and anxiety as consecutive mediators; ***$p < 0.001$

COVID-19 and the lockdown's impact were both associated with lower general wellbeing, anxiety and depression among Lebanese samples [58, 59]. Results of our study showed that higher PSMU was significantly associated with depression and anxiety, in line with previous findings [60–62]. These authors speculated that the reason for this association may be due to the fact that individuals who engage in online-activities in an excessive way, may neglect healthy aspects of their lives, which could contribute to depressive symptoms. Hence, excessive internet users may more be likely to replace their real-life interactions by online sites than the normal users. They were also found to have more depressive symptoms [61, 62]. A study conducted on Lebanese university students had found a significant association between potential internet addiction and insomnia, depression, anxiety and stress [63]. Moreover, a systematic review of 159 articles, found a bidirectional relationship between PSMU and depression and anxiety; depressed or anxious people may have a higher use of social media, whereas those using social media intensely or excessively may report greater depression or anxiety. The authors of this systematic review concluded that depression and anxiety can be both the causes and consequences of PSMU [64]. In an attempt to evaluate the association between PSMU and its correlates, a Lebanese study found an association between PSMU and anxiety and social phobia [65], in agreement with other international studies [66, 67]. PSMU was associated with an increased level of loneliness, where individuals presenting depressive symptoms may be more prone to use social media rather than face-to-face interactions [68–70]. Adolescents who spend less time in front of their screen and engage in more physical activities were found to have lower risks of reporting mental health problems [71].

Depression, anxiety and BN

Higher depression and anxiety were both associated with higher BN in the current study, consistent with the findings of a previous study [31]. These authors have found

that dizziness, unsteadiness, alterations in appetite and lack of sex were central in BN. Furthermore, 65% of women presenting for treatment of an ED also met the criteria for at least one comorbid anxiety disorder [30]. Previous authors demonstrated that, in addition to distorted body-related thoughts, maladaptive self-evaluative perfectionism - which has been linked to core components of social anxiety disorder – mediated the relationship between bulimic symptoms and social interaction anxiety and fear of public scrutiny, two significant components of social anxiety disorder [72]. As hypothesized by Mitchell and colleagues, the two most common comorbid disorders in BN, generalized and social anxiety, could lead patients with BN to develop an interest in their body weight and shape [73]. Individuals presenting depressive symptoms showed significantly higher symptoms of BN than those without a diagnosis of depression [74]. Improving adherence to and results of ED interventions remain significant priorities for patients with comorbid anxiety disorders as they typically have worse illness courses and outcomes [75]. One symptom that was found to bridge the association between depression, anxiety and BN was physical sensation, which explains how these three disorders may interact [31].

PSMU and BN

Our study results revealed that higher PSMU was directly associated with more BN, corroborating the results of a previous study [19]. One reason for the study's findings is that people who use social media more frequently are exposed to more pictures and messages that increase the chances of developing ED. The posting and viewing of images and videos are particularly prevalent on some social media platforms, including Instagram, Snapchat, Pinterest, and Tumblr [16, 19]. In Lebanon, the number of social media users at the start of 2022 was equivalent to 75.2% of the total population [76]. Users of social media platforms could be exposed to powerful visual content, such as images that might support the slender ideal [19]. On top of that, it is believed that Western media content and exposure has been shown to significantly affect body image and eating behavior by promoting a "culture of thinness", predicting disordered eating symptoms, body dissatisfaction and a drive to thinness in women [77]. This exposure to thin-ideal images culture was positively associated with body dissatisfaction, food restriction and ED symptoms, which may contribute to EDs [77, 78]. With the spread of social media use and network sites, this increase in the drive to thinness and body dissatisfaction could make teenagers and young adults more vulnerable to EDs, while playing a primordial role in disordered eating attitudes [79, 80]. To our knowledge, this is the first study that aimed to evaluate the mediation effect of depression and anxiety between BN and PSMU. Anxious and depressive temperaments as well as state anxiety, had a direct unmediated effect on the drive to thinness, which is a core body-related psychopathology of AN [81].

Body dissatisfaction and BN

The results of the current study showed a positive association between body dissatisfaction and BN, which is consistent with previous findings [82]. Individuals with higher levels of body dissatisfaction usually have higher levels of abnormal eating attitudes such as drive for thinness or fear of gaining weight [83], which lead researchers to identify body dissatisfaction as a risk factor for EDs [84].

Clinical implications

The findings of this study may help clinicians better understand the associated factors – depression, anxiety and PSMU that increase BN symptoms. They may serve as a first step to create early intervention strategies, such as Cognitive Behavior Therapy – Enhanced (CBT-E), which was proven to have an important impact on the reduction of EDs symptoms [85, 86]. As anxiety and depression were positively associated with BN, reducing their levels may in turn be associated with a decrease in BN levels; hence, other forms of treatment that tackle depression and anxiety may also be of use to reduce BN symptoms such as Cognitive Behavioral Therapy [87, 88], Schema Therapy [89], and Mindfulness-Based Interventions [90]. The need for campaigns and awareness about the harms of PSMU would also be needed in Lebanon.

Strengths and limitations

There are some limitations in our study. The data's cross-sectional nature limits the ability to pull causality conclusions. The use of a self-administered questionnaire and the under or over-estimation of a question pose a risk for information bias. There is also a risk of selection bias, given the nature of the sample enrollment and the fact that we cannot know the refusal rate. Furthermore, a residual confounding is still possible, despite the fact that we included several factors as potential confounders. Recruitment was completed entirely online due to security and health reasons in Lebanon. Moreover, it is recommended to conduct longitudinal or cross-sectional studies taking into consideration the association between time spent on SM and other variables while taking into consideration the content consumed while using social media. Although validated in Lebanon, the SMD scale was created to screen for the possible problematic social media use in participants but not for diagnosis, since

social media is not yet classified as an addiction or disorder according to the DSM-5.

Notwithstanding these limitations, the results represent preliminary evidence and could be considered as a baseline for future studies to investigate other variables associated with PSMU and BN in Lebanon. This study revealed important findings that encourage further exploration of BN and its correlates in Lebanon.

Conclusion

BN is a serious mental and physical illness that involves complex and damaging relationships with food, eating, exercise, and body image. Improved awareness might lead to earlier detection and treatment in these groups that suffer from an extra stigma of a 'young, Western, female-specific' psychiatric disorder. Additional investigations of BN and its correlates must strive to improve the comprehension of these associations' pathways through designs that allow drawing temporal frameworks, in order to efficiently treat this ED and prevent its negative outcomes. Futures studies should replicate the mediation analysis conducted in the current study, while taking into account EDs other than BN.

Abbreviations

BN	Bulimia nervosa
PSMU	Problematic social media use
ED(s)	Eating disorder(s)
AN	Anorexia nervosa
BED	Binge eating disorder

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Author contributions

SO and SH designed the study; CR and MS drafted the manuscript; SH carried out the analysis and interpreted the results; all authors reviewed the final manuscript and gave their consent. All authors read and approved the final manuscript.

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Availability of data and materials

All data generated or analyzed during this study are not publicly available due the restrictions from the ethics committee.

Declarations

Ethics approval and consent to participate

The Psychiatric Hospital of the Cross Ethics and Research Committee approved this study protocol (HPC-007-2021). Submitting the form online was considered equivalent to obtaining a written informed consent. All methods were performed in accordance with the relevant guidelines and regulations.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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The Welfare Effects of Social Media†

By Hunt Allcott, Luca Braghieri, Sarah Eichmeyer, and Matthew Gentzkow*

The rise of social media has provoked both optimism about potential societal benefits and concern about harms such as addiction, depression, and political polarization. In a randomized experiment, we find that deactivating Facebook for the four weeks before the 2018 US midterm election (*i*) *reduced online activity, while increasing offline activities such as watching TV alone and socializing with family and friends;* (*ii*) *reduced both factual news knowledge and political polarization;* (*iii*) *increased subjective well-being; and* (*iv*) *caused a large persistent reduction in post-experiment Facebook use. Deactivation reduced post-experiment valuations of Facebook, suggesting that traditional metrics may overstate consumer surplus.* (*JEL* D12, D72, D90, I31, L82, L86, Z13)

Social media have had profound impacts on the modern world. Facebook, which remains by far the largest social media company, has 2.3 billion monthly active users worldwide (Facebook 2018). As of 2016, the average user was spending 50 minutes per day on Facebook and its sister platforms Instagram and Messenger (Facebook 2016). There may be no technology since television that has so dramatically reshaped the way people get information and spend their time.

Speculation about social media's welfare impact has followed a familiar trajectory, with early optimism about potential benefits giving way to widespread concern about possible harms. At a basic level, social media dramatically reduce the cost of connecting, communicating, and sharing information with others. Given that interpersonal connections are among the most important drivers of happiness and

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well-being (Myers 2000; Reis, Collins, and Berscheid 2000; Argyle 2001; Chopik 2017), this could be expected to bring widespread improvements to individual welfare. Many have also pointed to wider social benefits, from facilitating protest and resistance in autocratic countries, to encouraging activism and political participation in established democracies (Howard et al. 2011, Kirkpatrick 2011).

More recent discussion has focused on an array of possible negative impacts. At the individual level, many have pointed to negative correlations between intensive social media use and both subjective well-being and mental health.[1] Adverse outcomes such as suicide and depression appear to have risen sharply over the same period that the use of smartphones and social media has expanded.[2] Alter (2018) and Newport (2019), along with other academics and prominent Silicon Valley executives in the "time well-spent" movement, argue that digital media devices and social media apps are harmful and addictive. At the broader social level, concern has focused particularly on a range of negative political externalities. Social media may create ideological "echo chambers" among like-minded friend groups, thereby increasing political polarization (Sunstein 2001, 2017; Settle 2018). Furthermore, social media are the primary channel through which misinformation spreads online (Allcott and Gentzkow 2017), and there is concern that coordinated disinformation campaigns can affect elections in the United States and abroad.

In this paper, we report on a large-scale randomized evaluation of the welfare impacts of Facebook, focusing on US users in the run-up to the November 2018 midterm elections. We recruited a sample of 2,743 users through Facebook display ads, and elicited their willingness-to-accept (WTA) to deactivate their Facebook accounts for a period of four weeks ending just after the election. We then randomly assigned the 61 percent of these subjects with WTA less than \$102 to either a Treatment group that was paid to deactivate, or a Control group that was not. We verified compliance with deactivation by regularly checking participants' public profile pages. We measured a suite of outcomes using text messages, surveys, emails, direct measurement of Facebook and Twitter activity, and administrative voting records. Less than 2 percent of the sample failed to complete the endline survey, and the Treatment group's compliance with deactivation exceeded 90 percent.

Our study offers the largest-scale experimental evidence available to date on the way Facebook affects a range of individual and social welfare measures. We evaluate the extent to which time on Facebook substitutes for alternative online and offline activities, with particular attention to crowd out of news consumption and face-to-face social interactions. We study Facebook's broader political externalities via measures of news knowledge, awareness of misinformation, political engagement, and political polarization. We study the impact on individual utility via measures of subjective well-being, captured through both surveys and text messages. Finally, we analyze the extent to which forces like addiction, learning, and projection bias may cause suboptimal consumption choices, by looking at how usage and valuation of Facebook change after the experiment.

[1] See, for example, Vanden Abeele et al. (2018); Burke and Kraut (2016); Ellison, Steinfield, and Lampe (2007); Frison and Eggermont (2015); Kross et al. (2013); Satici and Uysal (2015); Shakya and Christakis (2017); and Tandoc, Ferrucci, and Duffy (2015). See Appel, Gerlach, and Crusius (2016) and Baker and Algorta (2016) for reviews.

[2] See, for example, Twenge, Sherman, and Lyubomirsky (2016); Twenge and Park (2019); Twenge, Martin, and Campbell (2018); and Twenge et al. (2018).

Our first set of results focuses on substitution patterns. A key mechanism for effects on individual well-being would be if social media use crowds out face-to-face social interactions and thus deepens loneliness and depression (Twenge 2017). A key mechanism for political externalities would be if social media crowds out consumption of higher-quality news and information sources. We find evidence consistent with the first of these but not the second. Deactivating Facebook freed up 60 minutes per day for the average person in our Treatment group. The Treatment group actually spent less time on both non-Facebook social media and other online activities, while devoting more time to a range of offline activities such as watching television alone and spending time with friends and family. The Treatment group did not change its consumption of any other online or offline news sources and reported spending 15 percent less time consuming news.

Our second set of results focuses on political externalities, proxied by news knowledge, political engagement, and political polarization. Consistent with the reported reduction in news consumption, we find that Facebook deactivation significantly reduced news knowledge and attention to politics. The Treatment group was less likely to say they follow news about politics or the President, and less able to correctly answer factual questions about recent news events. Our overall index of news knowledge fell by 0.19 standard deviations. There is no detectable effect on political engagement, as measured by voter turnout in the midterm election and the likelihood of clicking on email links to support political causes. Deactivation significantly reduced polarization of views on policy issues and a measure of exposure to polarizing news. Deactivation did not statistically significantly reduce affective polarization (i.e., negative feelings about the other political party) or polarization in factual beliefs about current events, although the coefficient estimates also point in that direction. Our overall index of political polarization fell by 0.16 standard deviations. As a point of comparison, prior work has found that a different index of political polarization rose by 0.38 standard deviations between 1996 and 2018 (Boxell 2018).

Our third set of results looks at subjective well-being. Deactivation caused small but significant improvements in well-being, and in particular in self-reported happiness, life satisfaction, depression, and anxiety. Effects on subjective well-being as measured by responses to brief daily text messages are positive but not significant. Our overall index of subjective well-being improved by 0.09 standard deviations. As a point of comparison, this is about 25–40 percent of the effect of psychological interventions including self-help therapy, group training, and individual therapy, as reported in a meta-analysis by Bolier et al. (2013). These results are consistent with prior studies suggesting that Facebook may have adverse effects on mental health. However, we also show that the magnitudes of our causal effects are far smaller than those we would have estimated using the correlational approach of much prior literature. We find little evidence to support the hypothesis suggested by prior work that Facebook might be more beneficial for "active" users: for example, users who regularly comment on pictures and posts from friends and family instead of just scrolling through their news feeds.[3]

[3]Correlation studies on active versus passive Facebook use include Burke, Marlow, and Lento (2010); Burke, Kraut, and Marlow (2011); Burke and Kraut (2014); and Krasnova et al. (2013), and randomized experiments include Deters and Mehl (2013) and Verduyn et al. (2015).

Our fourth set of results considers whether deactivation affected people's demand for Facebook after the study was over, as well as their opinions about Facebook's role in society. As the experiment ended, participants reported planning to use Facebook much less in the future. Several weeks later, the Treatment group's reported usage of the Facebook mobile app was about 11 minutes (22 percent) lower than in Control. The Treatment group was more likely to click on a post-experiment email providing information about tools to limit social media usage, and 5 percent of the Treatment group still had their accounts deactivated nine weeks after the experiment ended. Our overall index of post-experiment Facebook use is 0.61 standard deviations lower in Treatment than in Control. In response to open-answer questions several weeks after the experiment ended, the Treatment group was more likely to report that they were using Facebook less, had uninstalled the Facebook app from their phones, and were using the platform more judiciously. Reduced post-experiment use aligns with our finding that deactivation improved subjective well-being, and it is also consistent with the hypotheses that Facebook is habit forming in the sense of Becker and Murphy (1988) or that people learned that they enjoy life without Facebook more than they had anticipated.

Deactivation caused people to appreciate Facebook's both positive and negative impacts on their lives. Consistent with our results on news knowledge, the Treatment group was more likely to agree that Facebook helps people to follow the news. About 80 percent of the Treatment group agreed that deactivation was good for them, but they were also more likely to think that people would miss Facebook if they used it less. In free response questions, the Treatment group wrote more text about how Facebook has both positive and negative impacts on their lives. The opposing effects on these specific metrics cancel out, so our overall index of opinions about Facebook is unaffected.

Our work also speaks to an adjacent set of questions around how to measure the economic gains from free online services such as search and media.[4] In standard models with consumers who correctly optimize their allocation of time and money, researchers can approximate the consumer surplus from these services by measuring time use or monetary valuations, as in Brynjolfsson and Oh (2012); Brynjolfsson, Eggers, and Gannamaneni (2018); Corrigan et al. (2018); and others. But if users do not understand the ways in which social media could be addictive or make them unhappy, these standard approaches could overstate consumer surplus gains. Sagioglu and Greitemeyer (2014) provides suggestive evidence: while their participants predicted that spending 20 minutes on Facebook would make them feel better, it actually caused them to feel worse. Organizations such as Time to Log Off argue that a 30-day "digital detox" would help people align their social media usage with their own best interest.

To quantify the possibility that deactivation might help the Treatment group to understand ways in which their use had made them unhappy, we elicited willingness-to-accept at three separate points, using incentive-compatible Becker-DeGroot-Marschak (1964) mechanisms. First, on October 11, we elicited WTA to deactivate Facebook for weeks 1–4 of the experiment, between October 12

[4] See, for example, Brynjolfsson and Saunders (2009); Byrne, Fernald, and Reinsdorf (2016); Nakamura, Samuels, and Soloveichik (2016); Brynjolfsson, Rock, and Syverson (2019); and Syverson (2017).

and November 8. We immediately told participants the amount that they had been offered to deactivate ($102 for the Treatment group, $0 for Control), and thus whether they were expected to deactivate over that period. We then immediately elicited WTA to deactivate Facebook for the next four weeks *after* November 8, i.e., weeks 5–8. When November 8 arrived, we then re-elicited WTA to deactivate for weeks 5–8. The Treatment group's change in valuation for weeks 5–8 reflects a time effect plus the effect of deactivating Facebook. The Control group's parallel valuation change reflects only a time effect. Thus, the difference between how Treatment versus Control change their WTAs for deactivation for weeks 5–8 reflects projection bias, learning, or other unanticipated experience effects from deactivation.[5]

After weighting our sample to match the average US Facebook user on observables, the median and mean willingness-to-accept to deactivate Facebook for weeks 1–4 were $100 and $180, respectively. These valuations are larger than most estimates in related work by Brynjolfsson, Eggers, and Gannamaneni (2018); Corrigan et al. (2018); Mosquera et al. (2018); and Sunstein (forthcoming). A standard consumer surplus calculation would aggregate the mean valuation across the estimated 172 million US Facebook users, giving $31 billion in consumer surplus from four weeks of Facebook. However, consistent with our other results that deactivation reduced demand for Facebook, deactivation caused WTA for weeks 5–8 to drop by up to 14 percent. This suggests that traditional consumer surplus metrics overstate the true welfare gains from social media, though a calculation that adjusts for the downward WTA revision would still imply that Facebook generates enormous flows of consumer surplus.

What do our results imply about the overall net welfare impact of Facebook? On the one hand, Facebook deactivation increased subjective well-being, and 80 percent of the Treatment group reported that deactivation was good for them. On the other hand, participants were unwilling to give up Facebook unless offered fairly large amounts of money: even after they had deactivated for four weeks, which should have allowed at least some learning or "detox" from addiction. It is not entirely clear whether one should prioritize the survey measures or monetary valuations as normative measures of consumer welfare. Benjamin et al. (2012) suggests that subjective well-being measures like ours are not a complete measure of what people are trying to maximize when they make decisions, but Bohm, Lindén, and Sonnegård (1997); Mazar, Kőszegi, and Ariely (2014); and other studies make clear that monetary valuations are not closely held and can be easily manipulated. We think of these tensions as fodder for future research.

Our results should be interpreted with caution, for several reasons. First, effects could differ with the duration, time period, or scale of deactivation. A longer period without Facebook might have less impact on news knowledge as people find alternative news sources, and either more or less impact on subjective well-being. Effects might be different for our pre-election deactivation than for deactivation in other periods. Furthermore, the effects of deactivating a large share of Facebook users

[5] This measurement connects to the literature on habit formation and projection bias, including Acland and Levy (2015); Becker and Murphy (1988); Becker, Grossman, and Murphy (1991); Busse et al. (2015); Charness and Gneezy (2009); Conlin, O'Donoghue, and Vogelsang (2007); Fujiwara, Meng, and Vogl (2016); Gruber and Kőszegi (2001); Hussam et al. (2016); Loewenstein, O'Donoghue, and Rabin (2003); and Simonsohn (2010).

would likely be different due to network effects, so our parameters are most relevant for individuals independently determining their own Facebook use. Second, our sample is not fully representative. Our participants are relatively young, well-educated, and left-leaning compared to the average Facebook user; we included only people who reported using Facebook more than 15 minutes per day; and people willing to participate in our experiment may also differ in unobservable ways. Third, many of our outcome variables are self-reported, adding scope for both measurement error and experimenter demand effects. However, Section IVF finds no evidence of demand effects, and our non-self-reported outcomes paint a similar picture to the survey responses.

The causal impacts of social media have been of great interest to researchers in economics, psychology, and other fields. We are aware of 12 existing randomized impact evaluations of Facebook.[6] The most closely related is the important paper Mosquera et al. (2018), which was made public the month before ours. That paper also uses Facebook deactivation to study news knowledge and well-being, finding results broadly consistent with those reported here. Online Appendix Table A1 details these experiments in comparison to ours. Our deactivation period is substantially longer and our sample size an order of magnitude larger than most prior experimental work, including Mosquera et al. (2018). We measure impacts on a relatively comprehensive range of outcomes, and we are the only one of these randomized trials to have submitted a pre-analysis plan. Given the effect sizes and residual variance in our sample, we would have been unlikely to have sufficient power to detect any effects if limited to the sample sizes in previous experiments. Our work also relates to quasi-experimental estimates of social media effects by Müller and Schwarz (2018) and Enikolopov, Makarin, and Petrova (2018).

Sections I through III present the experimental design, descriptive statistics, and empirical strategy. Section IV presents the impact evaluation, and Section V discusses measurement of the consumer surplus generated by Facebook.

I. Experimental Design

A. *Experiment Overview*

Figure 1 summarizes our experimental design and time line. We timed the experiment so that the main period of Facebook deactivation would end shortly after the 2018 US midterm elections, which took place on November 6. The experiment has eight parts: recruitment, pre-screen, baseline survey, midline survey, endline survey, post-endline survey, post-endline emails, and daily text messages.

Between September 24 and October 3, we recruited participants using Facebook ads. Our ad said, "Participate in an online research study about internet browsing and

[6] These studies sit within a broader media effects literature that uses experimental and quasi-experimental methods to quantify the effects of media technologies such as television, media providers such as Fox News, and content such as political advertising (Bartels 1993; Besley and Burgess 2001; DellaVigna and Kaplan 2007; Enikolopov, Petrova, and Zhuravskaya 2011; Gentzkow 2006; Gerber and Green 2000; Gerber et al. 2011; Gerber, Karlan, and Bergan 2009; Huber and Arceneaux 2007; Martin and Yurukoglu 2017; Olken 2009; and Spenkuch and Toniatti 2016). For reviews, see DellaVigna and Gentzkow (2010), Napoli (2014), Strömberg (2015), Enikolopov and Petrova (2015), and DellaVigna and La Ferrara (2015).

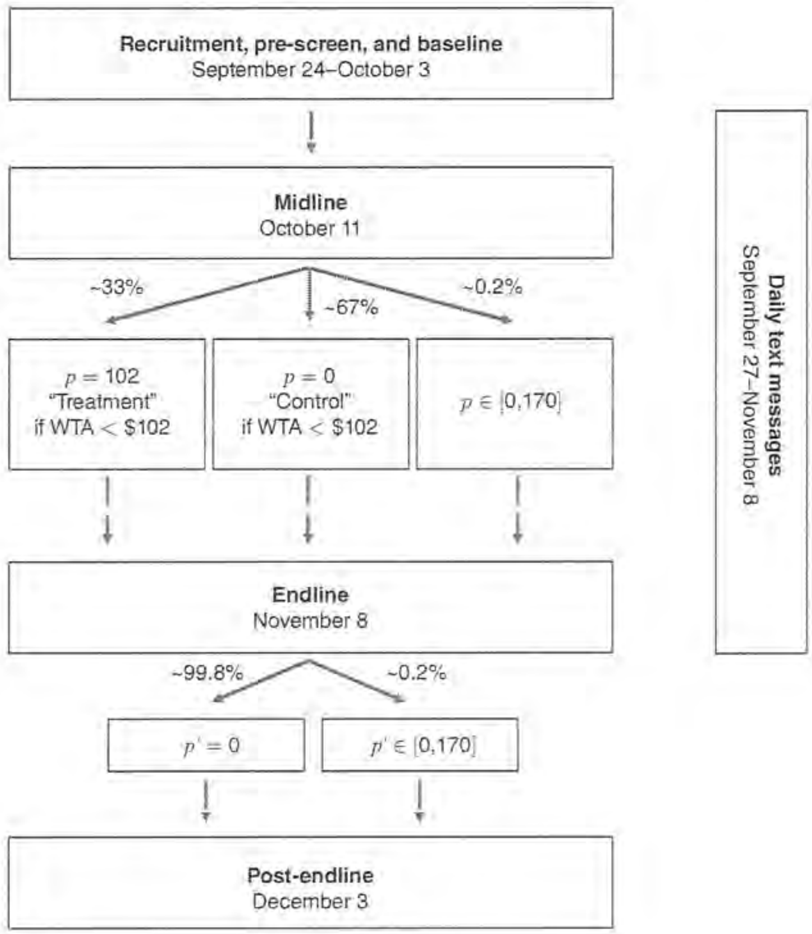


FIGURE 1. EXPERIMENTAL DESIGN

earn an easy $30 in electronic gift cards." Online Appendix Figure A1 presents the ad. To minimize sample selection bias, the ad did not hint at our research questions or suggest that the study was related to social media or Facebook deactivation. We targeted the ads by demographic cells in an attempt to gather an initial sample that was approximately representative of Facebook users on gender, age, college completion, and political ideology. A total of 1,892,191 unique users were shown the ad, of whom 32,201 clicked on it. This 1.7 percent click-through rate is about twice the average click-through rate on Facebook ads across all industries.[7]

Clicking on the ad took the participant to a brief pre-screen survey, which included several background demographic questions and the consent form. A total of 17,335 people passed the pre-screen, by reporting being a US resident born between the years 1900 and 2000 who uses Facebook more than 15 minutes and no more than 600 minutes per day. Of those people, 7,455 consented to participate in the study.

After completing the consent form, participants began the baseline survey. The baseline recorded email addresses, additional demographics, and a range of outcome

[7] Mark Irvine, "Facebook Ad Benchmarks for YOUR Industry." *WordStream*, August 27, 2019, https://www.wordstream.com/blog/ws/2017/02/28/facebook-advertising-benchmarks.

variables. We also asked for each participant's name, zip code, Twitter handle, and phone number ("in order for us to send you text messages during the study"), as well as the URL of their Facebook profile page (which we would use "solely to observe whether your Facebook account is active"). Finally, we informed people that we would later ask them to deactivate their accounts for two 24-hour periods, and confirmed their willingness to do so. (We required all participants regardless of treatment status to deactivate for these 24-hour periods to minimize selective attrition and to ensure that the valuations described below reflect value of Facebook access, not the fixed cost of the deactivation process.)

In all, 3,910 people finished the baseline survey and were willing to deactivate. Of those, 1,013 were dropped from the experiment because of invalid data (for example, invalid Facebook profile URLs) or low-quality baseline responses (for example, discrepancies between average daily Facebook usage reported in the pre-screen versus baseline survey, completing the survey in less than ten minutes, no text in short-answer boxes, and other patterns suggesting careless responses). The remaining 2,897 participants had valid baseline data, were included in our stratified randomization, and were invited to take the midline survey.

On October 11, we sent an email invitation to the midline survey. The survey first asked participants to deactivate their Facebook accounts for 24 hours and guided them through the process. The survey clearly explained what deactivation entailed and how we would monitor deactivation. Facebook allows users to deactivate and reactivate their accounts at any time. We informed participants that they could continue to use Facebook Messenger while deactivated, and that their profile and friend network would be unchanged when they reactivated. We emphasized that Facebook would automatically reactivate their account if they logged into the Facebook website or app, or if they actively logged into any *other* app using their Facebook login credentials.[8] We informed participants that "We will verify whether or not you deactivated your account by pinging the Facebook URL" that they had provided in the baseline survey.

The midline survey then used a Becker-DeGroot-Marschak (BDM) mechanism to elicit willingness-to-accept (WTA) to stay deactivated for four weeks rather than 24 hours.[9] We then revealed the BDM price offer. An additional 154 participants had dropped out before this point of the midline survey, leaving 2,743 who received their price offer. Participants whose WTA was strictly less than the price draw were informed that they should deactivate for the full four weeks after midline. Finally, the midline survey reminded people that we would again ask them to deactivate for

[8] A user's Facebook account automatically reactivates whenever the user actively logs into any other app using their Facebook login credentials. However, this does not fully preclude people from using other apps for which they had used Facebook to log in. People can continue using other apps if they are already logged in, can set up non-Facebook logins, or can log in with Facebook and then again deactivate their Facebook account.

[9] The survey explained, "The computer has randomly generated an amount of money to offer you to deactivate your Facebook account for the next 4 weeks. Before we tell you what the offer is, we will ask you the smallest offer you would be willing to accept. If the offer the computer generated is above the amount you give, we will ask you to deactivate for 4 weeks and pay you the offered amount if you do. If the offer is below that amount, we will not ask you to deactivate." We then asked several comprehension questions to make sure that participants understood the mechanism. We did not tell participants the distribution or support of the offer prices, both because we did not want to artificially truncate the distribution of elicited WTA and because prior studies have found that providing information on the bounds of the offer price distribution can affect BDM valuations (Bohm, Lindén, and Sonnegård 1997; Mazar, Kőszegi, and Ariely 2014).

24 hours after the endline survey, and used a second BDM mechanism to elicit WTA to stay deactivated for the four weeks after endline instead of just 24 hours. We refer to the four weeks after midline as "weeks 1–4," and the four weeks after endline as "weeks 5–8."

On November 8, two days after the midterm election, we sent an email invitation to the endline survey. The endline survey first measured the same outcome variables as the baseline survey. All questions were identical, with the exception of cases discussed in Section IC, such as using updated news knowledge questions and rephrasing questions about the midterm election to be in the past tense. We then asked all participants to again deactivate their Facebook accounts for the next 24 hours, and again elicited WTA to stay deactivated for the next four weeks (i.e., weeks 5–8) instead of the next 24 hours. Participants were told, "With a 50 percent chance we will require you to abide by the decision you made 4 weeks ago; with 50 percent chance we will ignore the decision you made 4 weeks ago and we will require you to abide by the decision you make today."

We gathered data from two post-endline emails. On November 20, we sent an email with links to information on ways to limit smartphone social media use, and on November 25, we sent an email with links to donate to, volunteer for, or sign petitions related to political causes. Clicks on these emails provide additional non-self-reported measures of interest in reducing social media use and political engagement. Online Appendix Figures A2 and A3 present the two emails.

On December 3, we invited participants to a short post-endline survey in which we asked how many minutes per day they had used the Facebook app on their smartphones in the past seven days. We asked participants with iPhones to report the Facebook app time reported by their phone's Settings app, and we asked other participants to estimate. We also asked several open-answer questions, such as "How has the way you use Facebook changed, if at all, since participating in this study?"

For the approximately six weeks between baseline and endline, we sent daily text message surveys to measure several aspects of subjective well-being in real time rather than retrospectively. We rotated three types of questions, measuring happiness, the primary emotion felt over the past ten minutes, and loneliness. Online Appendix Figure A4 presents the three questions.

We verified deactivation by checking each participant's Facebook profile page URL regularly at random times. While a user can limit how much content other people can see in their profiles, they cannot hide their public profile page, and the public profile URL returns a valid response if and only if their account is active.[10] This is thus our measure of deactivation. For all participants, we verified deactivation approximately once per day for the seven days before midline and all days between endline and the end of January 2019. Between midline and endline, we verified deactivation approximately four times per day for people who were supposed to be

[10] By default, Facebook profile URLs end in a unique number, which is the numeric ID for that person in the Facebook system. Users can update their default URL to be something customized, and they can change their customized URL as often as they want. In the baseline survey, participants reported their profile URLs, which could have been either the default or customized version. Shortly after the baseline survey, we checked if each participant's Facebook profile URL was valid by pinging it and looking in the page source for the string containing the person's numeric ID. If the numeric ID existed, we knew that the URL was valid. After that point, we used participants' numeric IDs to construct their default numeric URLs, which allowed us to correctly measure deactivation even if they changed their customized URL.

deactivated (i.e., the Treatment group) and once every four days for everyone else. During the post-midline and post-endline 24-hour deactivation periods, we generally verified deactivation within about six hours of when each participant completed the survey. If participants were not deactivated when they were supposed to be, our program immediately sent an automated email informing them that they should again deactivate as soon as possible, along with a survey asking them to explain why they were not deactivated.

All participants received \$5 per completed survey, paid via gift card immediately upon completion. All participants were told that they would receive a \$15 "completion payment" if they completed all surveys, responded to 75 percent of text messages, kept their accounts deactivated for the 24 hours after midline and endline, and, if the deactivation offer price was above their reported WTA, kept their accounts deactivated for the full period between midline and endline. The latter requirement (making the completion payment contingent on complying with the BDM's deactivation assignment) makes it a strictly dominant (instead of weakly dominant) strategy to truthfully report valuations in the BDM.[11] These payments were in addition to the \$102 that the Treatment group received in exchange for deactivation.

B. *Randomization*

We used the BDM mechanism described above to randomly assign participants to Facebook deactivation. Figure 1 illustrates the randomization. Participants with valid baseline data were randomized into three groups that determined the BDM offer price p for deactivation in weeks 1–4 (i.e., the weeks between midline and endline): $p = \$102$ (approximately 33 percent of the sample), $p = \$0$ (approximately 67 percent), and p drawn from a uniform distribution on $[\$0, \$170]$ (approximately 0.2 percent).[12] We balanced the $p = \$102$ and $p = \$0$ group assignments within 48 strata defined by age, average daily Facebook use, heavy versus light news use (those who get news from Facebook fairly often or very often versus never, hardly ever, or sometimes), active versus passive Facebook use, and Democrat, Republican, or independent party affiliation.

The effects of Facebook deactivation in weeks 1–4 are identified in the sample of participants who were allocated to $p = \$102$ or $p = \$0$ and were willing to accept less than \$102 to deactivate in weeks 1–4. We call this the "impact evaluation sample." Within the impact evaluation sample, we call $p = \$102$ the "Treatment" group, and $p = \$0$ the "Control" group.

For deactivation in weeks 5–8 (i.e., the four weeks after endline), 0.2 percent of participants were randomly selected to a BDM offer price drawn randomly from $p' \in [0, 170]$, while the remaining 99.8 percent received offer $p' = 0$. We balanced

[11] As discussed above, we did not inform participants of the BDM offer price distribution. Thus, more precisely, truthfully reporting valuations is a strictly dominant strategy only within the support of the offer price distribution that participants expected us to use.

[12] We chose \$102 because our pilot data correctly suggested that there would be a point mass of WTAs at \$100 and that it would maximize statistical power per dollar of cost to set an offer price just high enough to induce those participants to deactivate. We chose \$170 as the top of the uniform distribution because it was the maximum that we could pay participants without requiring tax-related paperwork.

this weeks 5–8 offer price p' between the weeks 1–4 offer price groups, so two participants who were offered $p = \$102$ and four participants who were offered $p = \$0$ were assigned to positive weeks 5–8 offers $p' \in [0, 170]$.

This approach allows us to maintain incentive compatibility in the BDM mechanism, have balance between Treatment and Control groups, and use a straightforward regression to estimate treatment effects of post-midline deactivation.

C. *Outcome Variables*

For the impact evaluation, we consider the outcome variables in the nine families described below. Online Appendix B presents survey question text and descriptive statistics for each outcome variable and moderator, grouped by family. We also construct indices that combine the outcome variables within each family, weighting by the inverse of the covariance between variables at endline, as described in Anderson (2008). In constructing these indices, we orient the variables so that more positive values have the same meaning: for example, more positive means "more polarized" in all cases. Outcomes to be multiplied by -1 are followed by "$\times (-1)$" in online Appendix B.

Substitute Time Uses.—At baseline and endline, we asked participants how many minutes per day they spent on Facebook on the average day in the past four weeks. At baseline, we also asked participants to report how much of their free time on the average day in the past four weeks they spent on various activities, ranging from using social media apps other than Facebook to spending time with friends and family in person. At endline, we asked how much time they spent on the same activities, "relative to what is typical for you." We phrased the questions in this way in order to more precisely detect changes in self-reported time use caused by the deactivation.

Social Interaction.—We have three measures of social interaction. The *friends met in person* variable is the natural log of 1 plus the number of friends seen in person in the last week, as measured by a survey question that asked participants to "list the first names of as many friends you met in person last week that you can think of in 1 minute." *Offline activities* is the number of offline activities (such as going out to dinner, spending time with your kids, etc.) that the person did at least once last week. *Diverse interactions* is an indicator for whether the respondent interacted with someone who voted the opposite way in the last presidential election plus an indicator for whether the respondent interacted with someone from another country in the last week.

Substitute News Sources.—At baseline, we asked participants how often they got news from different sources over the past four weeks, including Facebook, cable TV, print, and radio news, borrowing a standard survey question from the Pew Research Center (2018). At endline, we again asked how often they got news from those same sources, "relative to what is typical for you." For the participants who reported having a Twitter handle, we gathered data on number of tweets in the four weeks before baseline began and in the four weeks between midline and endline. This

allows a non-self-reported measure of one kind of potential substitution away from Facebook.[13]

News Knowledge.—In order to detect broad changes in news exposure, we asked participants how closely they followed politics, how closely they followed news about President Trump, and how many minutes per day they spent watching, reading, or listening to the news (including on social media) over the past four weeks.

In order to measure specific news knowledge, we included a 15-question news knowledge quiz. For each question, we gave a statement from the news in the past four weeks and asked participants to indicate if they thought the statement was true or false, or whether they were unsure. The order of the 15 statements was randomized. Seven of the statements were from news stories covered in the past four weeks in six news websites: *New York Times*, *Wall Street Journal*, Fox News, CNN, MSNBC, and *US News & World Report*, such as "The Trump administration set the maximum number of refugees that can enter the country in 2019 to 30,000." Three of the headlines were false modifications of articles from those same six news websites, such as "President Trump spoke at the funeral of former Arizona Senator John McCain, honoring the late McCain's wish." (In reality, it had been reported that President Trump was not invited to McCain's funeral.) The *news knowledge* variable is the count of true statements rated as true plus the count of false statements rated as false, plus one-half for every statement about which the respondent was "unsure." The final five statements were from fake news stories, rated false by third-party fact-checkers Snopes.com and Factcheck.org, that circulated heavily within a four-week period before the survey. The *fake news knowledge* variable is the count of fake statements correctly rated as "false" plus one-half for every statement about which the respondent was unsure. Online Appendix B presents the full news knowledge quizzes from both baseline and endline.

Political Engagement.—We have two measures of political engagement. First, we measure whether participants voted in the 2018 midterm election, by matching participants on name, birth year, and zip code to a voting database supplied to Stanford by L2, a voting data provider. See online Appendix C for details on the match process. Second, we measure whether participants clicked on any of the links in the post-endline politics email.

Political Polarization.—There are a variety of ways to measure political polarization (see, for example, Gentzkow 2016), and we use both standard and novel measures. First, we included standard "feeling thermometer" questions capturing how "warm or cold" participants felt toward the Democratic and Republican Parties and President Trump over the past four weeks. The *party affective polarization* variable is the respondent's thermometer warmth toward her own party minus her warmth toward the other party. For this and all other polarization variables, we include independents who lean toward a party, and we drop independents who do not lean toward either party.

[13] In our pre-analysis plan, we grouped this *number of tweets* variables in the substitute news sources family, but one might also think of it as a "substitute time use" because Twitter is not only used to read news.

Second, the *Trump affective polarization* variable is the thermometer warmth toward President Trump for Republicans, and -1 times the thermometer warmth toward President Trump for Democrats. Third, we asked respondents to list recent news events that made them angry at the Republican or Democratic Party. *Party anger* is the natural log of 1 plus the length (in characters of text) of her response about the other party minus the natural log of 1 plus the length of her response about her own party. Fourth, we asked people how often they saw news that made them better understand the point of view of the Republican Party, and a parallel question for news about the Democratic Party. *Congenial news exposure* is the respondent's answer about her own political party minus her answer for the other party.

Fifth, we asked opinions about nine current political issues, such as "To what extent do you think that free trade agreements between the US and other countries have been a good thing or a bad thing for the United States?" These nine questions were all adapted from recent Pew Center and Gallup opinion polls. The *issue polarization* variable reflects the extent to which the respondent's issue opinions align with the average opinion in her own party instead of the other party. Sixth, *belief polarization* reflects the extent to which the respondent's beliefs about current news events (from the news knowledge quiz described above) align with the average belief in her own party instead of the other party.[14] Finally, *vote polarization* measures the strength of preferences for the congressional candidate of the respondent's party in the midterm election.[15]

Subjective Well-Being.—There is a vast literature on measuring subjective well-being (see, for example, Kahneman et al. 2006), and we use standard measures from the literature. We modified existing scales in two ways. First, we asked questions in reference to the past four weeks, so as to increase our ability to detect changes as a result of Facebook deactivation. Second, in some cases we chose a subset of questions from standard multi-question scales in order to focus on areas of subjective well-being that might be most affected by Facebook.

The *happiness* variable is the average response to two questions from the Subjective Happiness Scale (Lyubomirsky and Lepper 1999), asking how happy participants were over the past four weeks and how happy they were compared to their peers. *Life satisfaction* is the sum of responses to three questions from the Satisfaction with Life Scale (Diener et al. 1985), such as the level of agreement with

[14] Specifically, for each issue or belief question q, we normalize responses by the standard deviation in the Control group, determine Democrats' and Republicans' average responses μ_q^D and μ_q^R, recenter so that $\mu_q^D + \mu_q^R = 0$, and resign so that $\mu^R > 0$. Define $\tilde{y}_{iq}$ as individual i's normalized, recentered, and re-signed response to question q, multiplied by -1 if i is a Democrat. Thus $\tilde{y}_{iq}$ reflects the strength of individual i's agreement with the average view of her party instead of the other party. For *issue polarization*, further define σ_q as the Control group within-person standard deviation of $\tilde{y}_{iq}$ for question q. This measures how much people's views change between baseline and endline, and allows us to place higher weight on issues about which views are malleable over the deactivation period. For belief polarization, let $\sigma_q = 1$. The issue and belief polarization measures are $Y_i = \sum_q \tilde{y}_{iq}\sigma_q$. Online Appendix Table A15 shows that the *issue polarization* results are nearly identical if we set $\sigma_q = 1$.

[15] Specifically, we asked "In the recent midterm elections, did you vote for the Republican Party's or for the Democratic Party's candidate for Congress in your district? (If you did not vote, please tell us whom you would have voted for.)" We code vote polarization as 0 for "other/don't know." For people who responded that they had (or would have) voted for the Republican or Democratic candidate, we then asked, "How convinced were you about whether to vote for the Republican candidate or the Democratic candidate?" In these cases, we code vote polarization on a scale from -1 (very convinced to vote for the Democratic candidate) to $+1$ (very convinced to vote for the Republican candidate), and then multiply by -1 for Democrats.

the statement, "During the past 4 weeks, I was satisfied with my life." *Loneliness* is the Three-Item Loneliness Scale (Hughes et al. 2004). Finally, *depressed, anxious, absorbed*, and *bored* reflect how much of the time during the past four weeks respondents felt each emotion, using questions from the European Social Survey well-being module (Huppert et al. 2009).

The daily text messages allowed us to measure the aspects of subjective well-being that are most important to record in the moment instead of retrospectively. This approach builds on the Experience Sampling Method of Csikszentmihalyi and Larson (2014) and Stone and Shiffman (1994). The variable *SMS happiness* is the answer to the question, "Overall, how happy do you feel right now on a scale from 1 (not at all happy) to 10 (completely happy)?" The variable *SMS positive emotion* is an indicator variable for whether the participant reports a positive emotion when asked, "What best describes how you felt over the last ten minutes?" with possible responses such as "angry," "worried," "loving/tender," etc. Finally, *SMS not lonely* uses the answer to the question, "How lonely are you feeling right now on a scale from 1 (not at all lonely) to 10 (very lonely)?"

Post-Experiment Facebook Use.—We have four measures of planned and actual post-experiment Facebook use. First, *planned post-study use change* is the extent to which participants plan to use Facebook more or less than they had before they started the study. (This was included only in the endline survey.) Second, *clicked time limit email* is an indicator for whether the respondent clicked any of the links in the post-endline social media time limit email. Third, *speed of reactivation* is -1 times the natural log of 1 plus the number of days that the participant's account remained deactivated between the post-endline 24-hour deactivation period and our most recent measurement on December 17. Fourth, *Facebook mobile app use* is the natural log of 1 plus the number of minutes per day that the participant reported using Facebook on their phone in the post-endline survey.

Opinions about Facebook.—We asked eight questions eliciting people's opinions about Facebook, such as "To what extent do you think Facebook is good or bad for society?" and "To what extent do you think Facebook makes people more or less politically polarized?" Each of these eight responses was on a ten-point scale. In the endline survey only, we also asked *Deactivation bad*: "As part of this study, you were asked to deactivate your Facebook account for [24 hours/4 weeks]. To what extent do you think that deactivating your account was good or bad for you?" Finally, we also included two open answer text boxes in which we asked people to write out the most important positive and negative impacts that Facebook has on their lives. The *positive impacts* and *negative impacts* variables are the natural log of 1 plus the count of characters in the respective text box.

Secondary Outcomes.—We also consider the following two outcomes, which we labeled as "secondary" in our pre-analysis plan. First, we consider the standard generic ballot question. At baseline, we asked "If the elections for US Congress were being held today, would you vote for the Republican Party's candidate or the Democratic Party's candidate for Congress in your district?" To increase precision,

TABLE 1—SAMPLE SIZES

Phase	Sample size
Recruitment and baseline	N = 1,892,191 were shown ads N = 32,201 clicked on ads N = 22,324 completed pre-screen survey N = 20,959 were from United States and born between 1900 and 2000 N = 17,335 had 15 < daily Facebook minutes ≤ 600 N = 7,455 consented to participate N = 3,910 finished baseline N = 2,897 had valid baseline and were randomized, of which:
Midline	N = 2,897 began midline N = 2,743 received a price offer, of which: N = 1,661 were in impact evaluation sample
Endline	N = 2,710 began endline N = 2,684 finished endline, of which: N = 1,637 were in impact evaluation sample
Post-endline	N = 2,067 reported Facebook mobile app use, of which: N = 1,219 were in impact evaluation sample

we then asked, "How convinced are you about whether to vote for the Republican or Democratic candidate?" At endline, we asked these questions in past tense, about whom the respondent did vote for in the 2018 midterm (or whom the respondent would have voted for had she voted, to avoid potentially selective non-response). The *voted Republican* variable is the strength of preferences for the Republican candidate. We labeled this outcome as secondary because we expected the estimates to be too imprecise to be of interest.

Second, we asked people to report whether they had voted (at endline) and planned to vote (at baseline) in the 2018 midterm. We labeled this as secondary because it is superseded by the administrative voting data from L2.

We also gathered contributions to political campaigns from the Federal Election Commission database. In our pre-analysis plan, we labeled this as secondary because very few Americans contribute to political campaigns, and we did not expect to be able to detect effects from four weeks of deactivation. Indeed, only one person in the impact evaluation sample donated to a political party between the October 2018 midline survey and July 2019. As a result, we deviate from the pre-analysis plan by dropping this from our analysis.

II. Descriptive Statistics

Table 1 shows sample sizes at each step of our experiment, from the 1.9 million Facebook users who were shown our ads, to the 1,661 subjects in the impact evaluation sample. Table 2 quantifies the representativeness of our sample on observables, by comparing the demographics of our impact evaluation sample to our estimate of the average demographics of adult Facebook users and to the US adult population. Comparing column 1 to columns 2 and 3, we see that our sample is relatively high-income, well-educated, female, young, and Democratic, and uses Facebook

TABLE 2—SAMPLE DEMOGRAPHICS

	Impact evaluation sample (1)	Facebook users (2)	US population (3)
Income under $50,000	0.40	0.41	0.42
College	0.51	0.33	0.29
Male	0.43	0.44	0.49
White	0.68	0.73	0.74
Age under 30	0.52	0.26	0.21
Republican	0.13		0.26
Democrat	0.42		0.20
Facebook minutes	74.52	45.00	

Notes: Column 1 presents average demographics for the impact evaluation sample: participants who were willing to accept less than $102 to deactivate Facebook for the four weeks after midline and were offered $p = \$102$ or $p = \$0$ to do so. Column 2 presents our estimate of average demographics of American adults with a Facebook account. The top five numbers in column 2 are inferred from a Pew Research Center (2018f) survey of social media use by demographic group. The bottom number in column 2 (the average of 45 minutes of Facebook use per day) is approximated on those basis of sources such as Facebook (2016) and Molla and Wagner (2018). Column 3 presents average demographics of American adults. The top five numbers are from the 2017 American Community Survey (US Census Bureau 2017), and the Republican and Democrat shares are from the 2016 American National Election Study (American National Election Studies 2016).

relatively heavily.[16] Online Appendix Table A14 shows that Treatment and Control are balanced on observables.

Table 3 documents very high response rates to the endline and post-endline surveys and subjective well-being text messages. Of the 580 people in the Treatment group, only 7 failed to complete the endline survey. Of the 1,081 people in the Control group, only 17 failed to complete endline. The average participant responded to 92 percent of daily text messages, well above the 75 percent required in order to receive the completion payment.[17] Treatment and Control have statistically equal response rates to the endline survey and subjective well-being text messages. A marginally significantly larger share of the Treatment group responded to the post-endline survey; this is less worrisome because Facebook mobile app use is the only variable from that survey for which we calculate treatment effects, and we show in online Appendix Table A13 that using Lee (2009) bounds to account for attrition does not change the conclusions. Finally, Table 3 also reports the high level of compliance with our deactivation treatment: treatment group participants were deactivated on 90 percent of checks between October 13 (the first day after the 24-hour post-midline deactivation period) and November 7 (the day before endline), against 2 percent for Control.

As described above, if Treatment group members were found to have active accounts, we sent an email informing them of this and asking them to promptly deactivate, along with a survey asking why they were not deactivated. From these

[16] In online Appendix Figures A17, A18, A19, and A20, we find that the two demographic variables that we prespecified as moderators, age and political party, do not appear to systematically moderate treatment effects. Furthermore, Figure 9 provides no systematic evidence that the effects vary for people who use Facebook more versus less heavily before baseline. This suggests that reweighting the sample for representativeness on these observables would not substantively change the estimated effects, although it would increase the standard errors.

[17] Online Appendix Figure A26 shows the text message response rate by day (response rates declined slightly over the course of the experiment) and shows that Treatment and Control response rates are statistically balanced in all days of the deactivation period.

TABLE 3—SURVEY RESPONSE AND TREATMENT COMPLIANCE RATES

Variable	Treatment mean/SD (1)	Control mean/SD (2)	t-test p-value (1) − (2)
Completed endline survey	0.99 (0.11)	0.98 (0.12)	0.54
Share of text messages completed	0.92 (0.20)	0.93 (0.18)	0.45
Completed post-endline survey	0.95 (0.23)	0.92 (0.26)	0.07
Share days deactivated	0.90 (0.29)	0.02 (0.13)	0.00
Observations	580	1,081	

Notes: Columns 1 and 2 present survey response and treatment compliance rates for the Treatment and Control groups in the impact evaluation sample: participants who were willing to accept less than \$102 to deactivate Facebook for the four weeks after midline and were offered $p = \$102$ or $p = \$0$ to do so. Column 3 presents p-values of tests of differences in response rates between the two groups.

surveys, along with email interactions and formal qualitative interviews following our summer 2018 pilot study, we conclude that most Treatment group members who did reactivate fall into one of two groups. The first group consists of a small number of users who changed their mind about participating in the experiment and reactivated intentionally. The second group consists of users who briefly reactivated by accident, for example because they logged in to another app or online service using their Facebook account credentials.

Online Appendix Figure A27 shows the cumulative distribution of the share of time deactivated for the Treatment group, and online Appendix Figure A28 shows the distribution of reasons for deactivation among those for whom this share was less than 1. Together, these figures suggest that the small group of intentional reactivators accounts for the vast majority of Treatment group noncompliance. Given this, combined with the fact that the Control group was also found to be deactivated for a small share of weeks 1–4, we will analyze the experiment as a randomized encouragement design.

III. Empirical Strategy

A. *Pre-Analysis Plan*

We submitted our pre-analysis plan on October 12, as this was the final day before the Treatment and Control groups could have begun to differ. We submitted a slightly updated pre-analysis plan on November 7, the day before endline, with only one substantive change: on the basis of data on reasons for non-compliance described above, we specified that our primary specifications would use IV estimates instead of intent-to-treat estimates. The pre-analysis plan specified three things. First, it specified the outcome variables and families of outcome variables as described above, including which specific variables are included in the index for

each family and which outcomes are "secondary." Versions of Figures 2, 3, 5, 6, 7, and 12 appear as figure shells in the pre-analysis plan, although we changed some variable labels as well as the order in which we present the families of outcome variables for expositional purposes. Second, the pre-analysis plan specified the moderators we use when testing for heterogeneous treatment effects, including which moderators are "secondary." Third, it specified the two regression specifications and the estimation sample as described below.

B. *Empirical Strategy*

To estimate the local average treatment effect (LATE) of Facebook deactivation, define Y_i as some outcome measured at endline, and $\mathbf{Y}_i^b$ as a vector including the baseline value of the outcome and the baseline value of the index that includes the outcome.[18] Define D_i as the percent of deactivation checks between October 13 and November 7 that person i is observed to be deactivated. Define $T_i \in \{1, 0\}$ as a Treatment group indicator, and ν_s as the vector of the 48 stratum dummies. We estimate local average treatment effects of deactivation using the following regression:

$$Y_i = \tau D_i + \rho \mathbf{Y}_i^b + \nu_s + \varepsilon_i, \tag{1}$$

instrumenting for D_i with T_i. In equation (1), τ measures the local average treatment effect of deactivation for people induced to deactivate by the promised \$102 payment.[19]

The base sample for all regressions is the "impact evaluation sample": again, participants who were willing to accept less than \$102 to deactivate in weeks 1–4 (the four weeks after midline) and were offered $p = \$102$ or $p = \$0$ to do so. For the political polarization outcomes, the sample includes only Democrats and Republicans, as well as independents who lean toward one party or the other. Sample sizes sometimes differ across outcomes due to missing data: for example, the post-endline survey has higher non-response than the endline survey, and many participants do not have Twitter accounts.

We use robust standard errors in all regressions.

[18] $\mathbf{Y}_i^b$ excludes the baseline value of the outcome for outcomes such as clicks on post-endline emails that do not have a baseline value. $\mathbf{Y}_i^b$ excludes the baseline index when Y_i is not included in an index. When Y_i is an index, $\mathbf{Y}_i^b$ is simply the baseline value of the index.

[19] Facebook deactivation might have a larger impact for people who use Facebook more. Define H_i as person i's average daily hours of Facebook use reported at baseline, winsorized at 120 minutes. We can also estimate the local average treatment effect of deactivation *per hour of daily Facebook use avoided* using the following regression:

$$Y_i = \tau D_i H_i + \beta H_i + \rho \mathbf{Y}_i^b + \nu_s + \varepsilon_i, \tag{2}$$

analogously instrumenting for $D_i H_i$ with $T_i H_i$.

If effects of deactivation are indeed linear in avoided hours of Facebook use, then equation (2) could provide more statistical power than equation (1). On the other hand, if effects are closer to constant in baseline usage and/or H_i is measured with error, then equation (1) will offer more power. In our pre-analysis plan, we specified that we would make either equation (1) or equation (2) our primary specification, depending on which delivered more power. In reality, the results are very similar. Therefore, we focus on equation (1) because it is simpler. Online Appendix E presents results using equation (2).

IV. Impact Evaluation

This section presents treatment effects of Facebook deactivation. The following subsections present estimates for four groups of outcomes: substitution, news and political outcomes, subjective well-being, and post-experiment Facebook use and opinions. We then present heterogeneous treatment effects. Finally, we provide evidence on experimenter demand effects.

In the body of the paper, we present figures with local average treatment effects and 95 percent confidence intervals from estimates of equation (1), with outcome variables Y_i normalized so that the Control group standard deviation equals 1. Online Appendix Tables A10 and A11 provide numerical regression results for all individual outcome variables in both normalized (standard deviation) units, as in the figures, and unnormalized (original) units. Online Appendix Table A12 provides numerical regression results for all nine summary indices. These tables also provide unadjusted p-values and "sharpened" False Discovery Rate (FDR)-adjusted p-values following the procedure of Benjamini, Krieger, and Yekutieli (2006), as outlined by Anderson (2008). The unadjusted p-values are appropriate for readers with a priori interest in one specific outcome. The FDR-adjusted p-values for the individual outcomes limit the expected proportion of false rejections of null hypotheses across all individual outcomes reported in the paper, while the FDR-adjusted p-values for the indices limit the expected proportion of false rejections of null hypotheses across the nine indices. The sharpened FDR-adjusted p-values are less conservative than the unadjusted p-values for p-values greater than about 0.15, and more conservative for unadjusted p-values less than that.

A. *Substitutes for Facebook*

Figure 2 presents treatment effects on substitutes for Facebook: substitute time uses, social interactions, and substitute news sources. Substitution is of interest for two reasons. First, our treatment entails deactivating Facebook *and* also reallocating that time to other activities. Understanding that reallocation is thus crucial for conceptually understanding the "treatment." Second, this substitution helps to understand mechanisms for key effects. One central mechanism through which Facebook might affect psychological well-being is by crowding out face-to-face interactions. However, it's also possible that when people deactivate, they primarily devote their newly available time to other solitary pursuits. Furthermore, a central mechanism for possible political externalities is that social media use crowds out consumption of higher-quality news. However, it's also possible that when people deactivate, they simply get less news overall instead of substituting to other news sources.

The top group of outcomes in Figure 2 measures self-reported time use. Facebook usage was reported in minutes. For all other activities, the endline survey asked respondents how much time they spent on the activity in the last four weeks relative to what is typical for them, on a five-point scale from "A lot less" to "A lot more." For all time use outcomes, "Same" is the average answer in the Control group.

The first row confirms that the treatment indeed reduced Facebook use as intended. At endline, the Control group reported that they had used Facebook for an average of 59.53 minutes per day over the past four weeks, and the local average

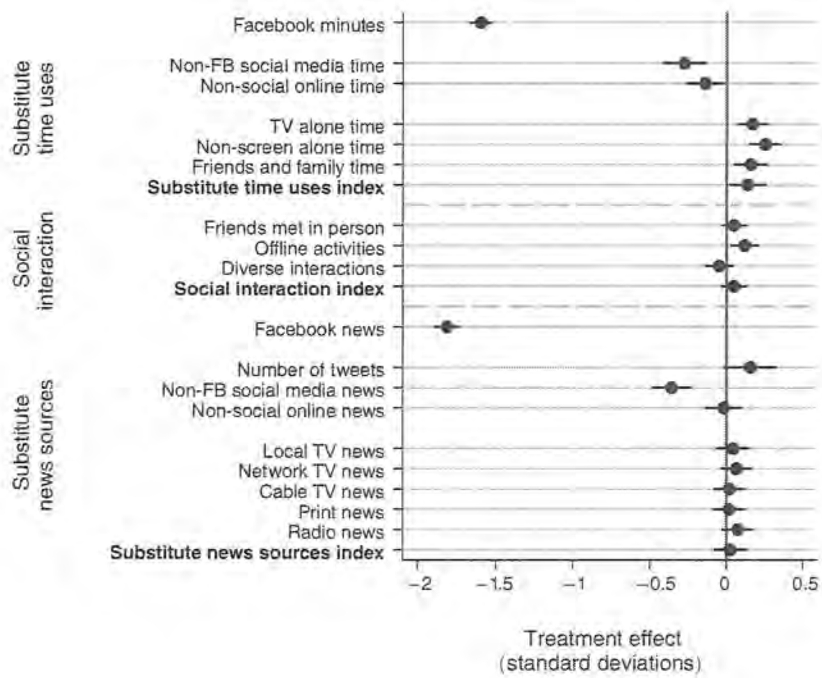


Figure 2. Substitutes for Facebook

Notes: This figure presents local average treatment effects of Facebook deactivation estimated using equation (1). All variables are normalized so that the Control group endline distribution has a standard deviation of 1. Error bars reflect 95 percent confidence intervals. See Section IC for variable definitions. *Facebook minutes* is not included in the substitute time uses index, and *Facebook news* is not included in the substitute news sources index, so we visually separate these two variables from the other variables in their respective families. We also visually separate online and offline time uses and news sources, although all online and offline substitutes enter their respective indexes.

treatment effect of deactivation is 59.58 minutes per day.[20] As shown in Figure 2, this corresponds to a reduction of 1.59 standard deviations.

We find that Facebook deactivation *reduced* time devoted to other online activities. Time using non-Facebook social media falls by a quarter point on our five-point scale (0.27 SD), and time on non-social online activities falls by 0.12 points (0.14 SD). Thus, Facebook appears to be a complement rather than a substitute for other online activities. This makes sense to the extent that deactivating Facebook makes people less likely to be using their phones or computers in the first place, and less likely to follow Facebook links that direct to non-Facebook sites (e.g., a news website or Twitter post). Furthermore, the Treatment group may have avoided logging into other apps such as Spotify and Tinder because we had informed participants that using Facebook to actively log into other apps would reactivate Facebook.

Rows 4–7 of Figure 2 suggest that the 60 minutes freed up by not using Facebook, as well as the additional minutes from reductions in other online activities, were

[20] Online Appendix Table A5 reports baseline means of our time use variables. The mean of self-reported Facebook minutes at baseline is 74.5 minutes per day, and the mean of reported minutes using the Facebook mobile app at baseline is 60 minutes per day.

allocated to both solitary and social activities offline. Solitary television watching increases by 0.17 points on our scale (0.17 SD), other solitary offline activities increase by 0.23 points (0.25 SD), and time devoted to spending time with friends and family increases by 0.14 points (0.16 SD). The substitute time uses index, which does not include *Facebook minutes*, shows an increase in overall non-Facebook activities. All of the online and offline time use effects are highly significant with and without adjustment for multiple hypothesis testing.

The middle group of outcomes in Figure 2 contains measures of social interaction. Deactivation increased the count of offline activities that people reported doing at least once last week by about 0.18 (0.12 SD). Online Appendix Figure A29 shows that the specific activities with the largest point estimates are going out to dinner, getting together with friends, and spending time with parents. The point estimates for the other offline activities we measure (going to the cinema, talking to friends on the phone, going to a party, going shopping, and spending time with your kids) are all very close to zero. Notwithstanding the positive effects on *offline activities*, there are no statistically significant effects on the number of friends that participants listed as having met in person last week, or on *diverse interactions* (whether or not they interacted with someone who voted differently in the last presidential election or interacted with someone from another country). We find no effects on the social interaction index, although the point estimate is positive.

The bottom group of outcomes in Figure 2 measures news consumption. As with the substitute time uses, the endline survey asked participants how much time they spent getting news from each source in the last four weeks relative to what is typical for them; "Same" is again the average answer in the Control group. As expected, Facebook deactivation substantially reduced the extent to which people said they relied on Facebook as a news source. Consistent with the time use results, the Treatment group also got substantially less news from non-Facebook social media sites (0.36 SD). The point estimates for print, radio, and TV news are all positive but statistically insignificant. Facebook deactivation has a positive but insignificant effect on Twitter use. As we discuss below in the news knowledge results, deactivation reduced the total time subjects report spending consuming news by 8 minutes per day, or 15 percent of the Control group mean of 52 minutes.

Overall, these results suggest that Facebook is a substitute for offline activities but a complement to other online activities. This suggests the possibility that Facebook could reduce subjective well-being by reducing in-person interactions, but also impose positive political externalities by increasing news knowledge. Below, we test these possibilities more directly.

B. *Effects on News and Political Outcomes*

Figure 3 presents treatment effects on news and political outcomes: news knowledge, political engagement, and political polarization. News knowledge and political engagement are of interest because well-functioning democratic societies fundamentally rely on well-informed voters who actually show up to the polls to vote. Political polarization is of interest because it is may make democratic decision making less efficient, and may lead citizens to perceive democratic outcomes as less legitimate (Iyengar, Sood, and Lelkes 2012; Iyengar and Westwood 2015).

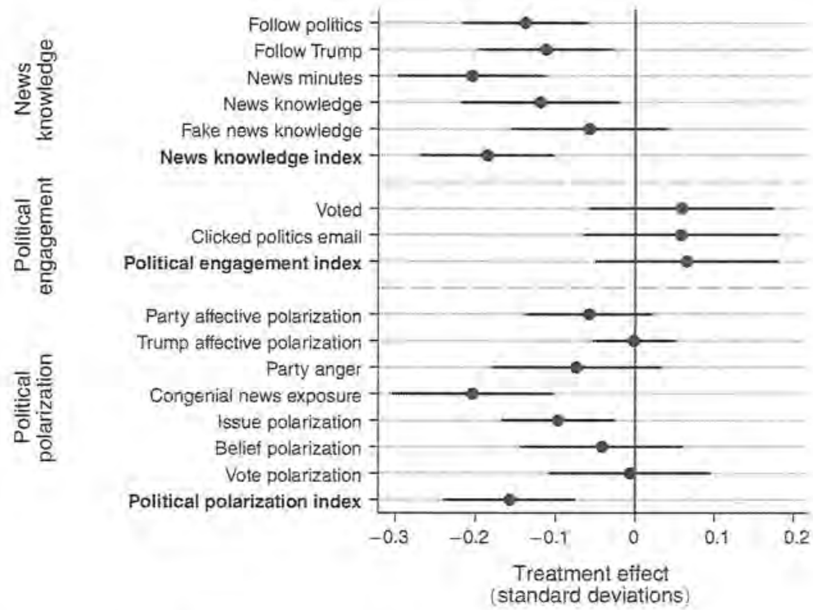


Figure 3. Effects on News and Political Outcomes

Notes: This figure presents local average treatment effects of Facebook deactivation estimated using equation (1). All variables are normalized so that the Control group endline distribution has a standard deviation of 1. Error bars reflect 95 percent confidence intervals. See Section IC for variable definitions.

Deactivation caused substantial reductions in both self-reported attention to news and directly measured news knowledge. The top three rows show that deactivation reduced how much people reported they followed news about politics and about President Trump (by 0.14 and 0.11 SD, respectively), as well as the average minutes per day spent consuming news (a drop of 8 minutes per day, or 15 percent of the control group mean). Accuracy on our news knowledge quiz fell by 0.12 standard deviations.[21] Tangibly, the Control group answered an average of 7.26 out of the 10 news knowledge questions correctly (counting "unsure" as one-half correct), and deactivation reduced this average by 0.14. There is no detectable effect on fake news knowledge, possibly reflecting the limited reach of even the highly shared fake news items included in our survey. Overall, deactivation reduced the news knowledge index by about 0.19 standard deviations.

There are no statistically detectable effects on political engagement. As reported in online Appendix Tables A10 and A11, the point estimates suggest that deactivation increased turnout by three percentage points according to the administrative data and decreased turnout by three percentage points according to the self-reported

[21] Online Appendix G presents more analysis of the effects on news knowledge, including effects on each individual news knowledge and fake news knowledge question. All but one of the point estimates for the ten news knowledge questions is negative. The news knowledge questions with the largest effects involve correctly responding that Elizabeth Warren's DNA test had revealed Native American ancestry and that Jeff Sessions had resigned at President Trump's request. There was also a statistically significant difference in knowledge about one fake news story: the Treatment group was less likely to correctly respond that Cesar Sayoc, the suspect in an act of domestic terrorism directed at critics of President Trump, was not a registered Democrat.

data, and neither estimate is statistically different from zero. Similarly, the Treatment and Control groups are statistically equally likely to have clicked on any link in the post-endline politics email. Online Appendix Figure A35 does show a marginally significant negative effect on *voted Republican*, suggesting that deactivation may have reduced support for Republican congressional candidates. The unadjusted p-value is 0.06, the sharpened FDR-adjusted p-value is 0.08, and we had labeled this as a "secondary outcome" in our pre-analysis plan.

Prior research has shown that people tend to be exposed to ideologically congenial news content in general (Gentzkow and Shapiro 2011) and on Facebook in particular (Bakshy, Messing, and Adamic 2015). Thus, the finding above that deactivation reduced news exposure naturally suggests that deactivation might have also reduced political polarization.

Indeed, deactivation did reduce political polarization. Point estimates are negative for all polarization measures. The largest and most significant individual effect is on *congenial news exposure*: deactivation decreased the number of times that people reportedly saw news that made them better understand the point of view of their own political party relative to the other party. Deactivation also decreased issue polarization, which Fiorina and Abrams (2008) singles out as the "most direct" way of measuring polarization.[22] Online Appendix Table A10 shows that both of these effects are highly significant after adjusting for multiple hypothesis testing. The other measures with the largest point estimates are *party anger* and *party affective polarization*, although these individual effects are not statistically significant. Overall, deactivation reduced the political polarization index by about 0.16 standard deviations.[23]

Figure 4 illustrates how deactivation reduced issue polarization, by plotting the distribution of "issue opinions" for Democrats and Republicans in Treatment and Control at endline. Our *issue opinions* measure exactly parallels the *issue polarization* variable used in the regressions, except that we keep opinions on a left-to-right scale, with more negative indicating more agreement with the average Democratic opinion, and more positive indicating more agreement with the average Republican opinion. (By contrast, the issue polarization variable multiplies Democrats' responses by -1, so that a more positive value reflects more agreement with the average opinion in one's political party.) We then normalize *issue opinions* to have a standard deviation of 1 in the Control group. The figure shows that deactivation moves both Democrats and Republicans visibly toward the center. In the Control group, the issue opinions of the average Democrat and the average Republican differ by 1.47 standard deviations. In the Treatment group, this difference is 1.35 standard deviations: about 8 percent less.

Are these polarization effects large or small? As one benchmark, we can compare these effects to the increase in political polarization in the United States since 1996.

[22] Online Appendix Figure A30 presents results for each of the issue polarization questions. The issues for which deactivation caused the largest decrease in polarization were the direction of racial bias in policing and whether the Mueller investigation is biased.

[23] Like all of our outcome families, the polarization index includes a range of different outcomes with different interpretations. Exposure to congenial news is conceptually different from affective polarization and issue polarization. Online Appendix Table A16 shows that the effect on the political polarization index is robust to excluding each of the seven individual component variables in turn, although the point estimate moves toward zero and the unadjusted p-value rises to 0.09 when omitting *congenial news exposure*.

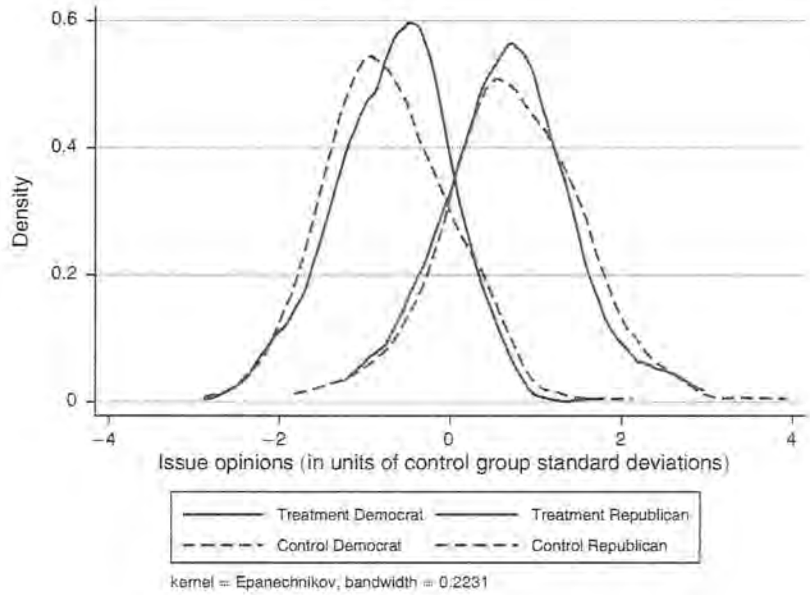


FIGURE 4. ISSUE OPINIONS BY PARTY AT ENDLINE

Notes: This figure presents kernel density plots of issue opinions for Democrats and Republicans in Treatment and Control at endline. Issue opinions are attitudes about nine current political issues on a scale from −5 to +5, such as "To what extent do you think that free trade agreements between the US and other countries have been a good thing or a bad thing for the United States." See online Appendix B for a list of all nine issue questions. To construct the *issue opinions* measure, for each issue question q, we normalize responses by the standard deviation in the Control group, determine Democrats' and Republicans' average responses μ_q^D and μ_q^R, recenter so that $\mu_q^D + \mu_q^R = 0$, and resign so that $\mu^R > 0$. Define $\tilde{y}_{iq}$ as individual i's normalized, recentered, and re-signed response to question q. Thus $\tilde{y}_{iq}$ reflects the strength of individual i's agreement with the average Republican. Define σ_q as the Control group within-person standard deviation of $\tilde{y}_{iq}$ for question q. This measures how much people's views change between baseline and endline, and allows us to place higher weight on issues about which views are malleable over the deactivation period. The preliminary *issue opinion* measure is $Y_i = \sum_q \tilde{y}_{iq}\sigma_q$, and the final *issue opinion* measure plotted in the figure is Y_i divided by the Control group standard deviation.

well before the advent of social media. Using data from the American National Election Studies, Boxell (2018) calculates that the change in a different index of polarization measures increased by 0.38 standard deviations between 1996 and 2016. The 0.16 standard deviation effect of Facebook deactivation on political polarization in our sample is about 42 percent as large as this increase.[24]

Overall, these results suggest that Facebook plays a role in helping people stay informed about current events, but also increases polarization, particularly of views on political issues.

[24] Specifically, Boxell's polarization index increased by 0.269 units from 1996–2016, and the standard deviation of Boxell's polarization index across people in 2016 is 0.710 units, so political polarization increased by $0.269/0.71 \approx 0.379$ standard deviations over that period. Of course, this benchmarking exercise does not imply that political polarization in the United States would have increased by one-third less in the absence of Facebook, for many reasons. For example, the treatment effects in our sample from a four-week deactivation are unlikely to generalize to the US population over Facebook's 15-year life. Furthermore, some of our polarization measures are unique to our study. The one measure that appears in both Boxell's index and our index, *party affective polarization*, rose by 0.18 standard deviations between 1996 and 2016. Our point estimate of −0.06 standard deviations is about one-third of this amount, although this estimate is not statistically different from zero.

C. *Effects on Subjective Well-Being*

Figure 5 presents estimates of effects on subjective well-being (SWB). These outcomes are of interest because, as discussed in the introduction, many studies show cross-sectional or time-series correlations between social media use and well-being, and on this basis researchers have speculated that social media may have serious adverse effects on mental health. The outcomes are re-signed so that more positive represents better SWB: for example, the "depressed" variable is multiplied by (-1).

We find that deactivation indeed significantly increases SWB. All but one of the ten point estimates are positive. The magnitudes are relatively small overall, with the largest and most significant effects on *life satisfaction* (0.12 SD), *anxiety* (0.10 SD), *depression* (0.09 SD), and *happiness* (0.08 SD).[25] All of these effects remain significant after adjusting for multiple hypothesis testing. The text message based measures of happiness are not significantly different from zero, with positive point estimates ranging from 0.01 SD to 0.06 SD. Deactivation improved our overall SWB index by 0.09 standard deviations.

Are these subjective well-being effects large or small? As one benchmark, we can consider the effect sizes in their original units, focusing on the measures with the largest effects. *Happiness* is the average response to two questions (for example, "Over the last 4 weeks, I think I was ...") on a scale from 1 (not a very happy person) to 7 (a very happy person). The Control group endline average is 4.47 out of a possible 7, and deactivation caused an average increase of 0.12. *Life satisfaction* is the extent of agreement with three questions (for example, "During the past four weeks, I was satisfied with my life") on seven-point Likert scales from "strongly disagree" to "strongly agree." The Control group endline average is 12.26 out of a possible 21, and deactivation caused an average increase of 0.56. *Depressed* and *anxious* are responses to the question, "Please tell us how much of the time during the past four weeks you felt [depressed/anxious]," where 1 is "None or almost none of the time" and 4 is "All or almost all of the time." The average responses are 2.99 and 2.60, respectively, and deactivation caused average increases of 0.08 and 0.09.

As a second benchmark, a meta-analysis of 39 randomized evaluations finds that positive psychology interventions (i.e., self-help therapy, group training, and individual therapy) improve subjective well-being (excluding depression) by 0.34 standard deviations and reduce depression by 0.23 standard deviations (Bolier et al. 2013). Thus, deactivating Facebook increased our subjective well-being index by about 25–40 percent as much as standard psychological interventions.

As a third benchmark, online Appendix Table A17 presents a regression of our baseline SWB index on key demographics (income, college completion, gender, race, age, and political party). College completion is conditionally associated with 0.23 standard deviations higher SWB. Thus, the effect of deactivating Facebook is just over one-third of the conditional difference in subjective well-being between college graduates and everyone else. The table also shows that

[25] Online Appendix Figure A34 presents results for the individual questions within the *happiness*, *life satisfaction*, and *loneliness* scales.

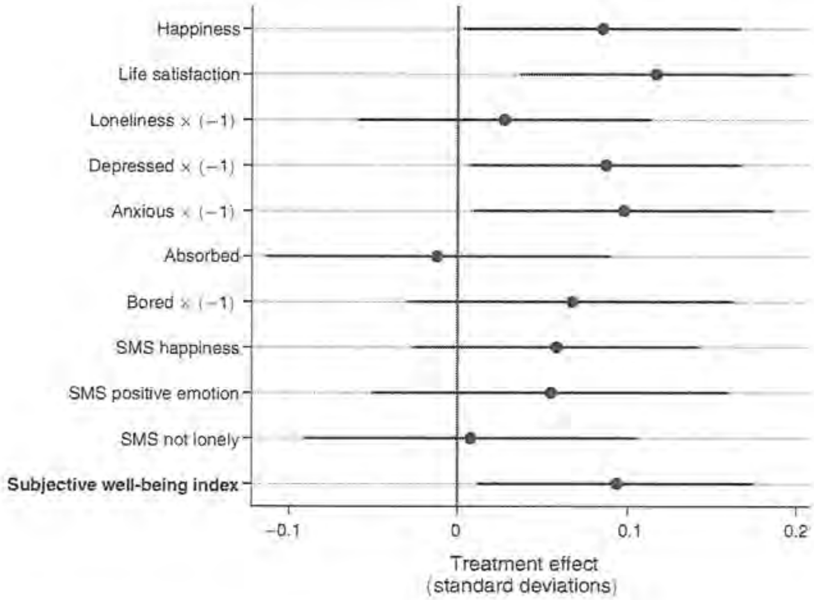


Figure 5. Effects on Subjective Well-Being

Notes: This figure presents local average treatment effects of Facebook deactivation estimated using equation (1). All variables are normalized so that the Control group endline distribution has a standard deviation of 1. Error bars reflect 95 percent confidence intervals. See Section IC for variable definitions.

a \$10,000 increase in income is conditionally associated with a 0.027 standard deviation increase in SWB. Thus, the effect of deactivating Facebook is equal to the conditional difference in subjective well-being from about \$30,000 additional income. This income equivalent is large because "money doesn't buy happiness": although income is correlated with SWB, the slope of that relationship is not very steep.

Online Appendix Figure A31 presents effects on the SMS outcomes by week of the experiment, to test whether the effects might have some trend over time. None of the effects on any of the three outcomes is statistically significant in any of the four weeks. The point estimates do not systematically increase or decrease over time, and if anything, the point estimates are largest in the first week. This suggests that the effects of a longer deactivation might not be different.

We can also compare our SWB effects to what we would have estimated using the kind of correlational approach taken by many previous non-experimental studies. These studies often have specific designs and outcomes that don't map closely to our paper, so it is difficult to directly compare effect sizes with other papers. We can, however, replicate the empirical strategy of simple correlation studies in our data, and compare our cross-sectional correlations to the experimental results. To do this, we regress SWB outcomes at baseline on daily average Facebook use over the past four weeks as of baseline, divided by the local average treatment effect of deactivation on daily average Facebook use between midline and

endline, so that the coefficients are both in units of average use per day over the past four weeks.[26]

The baseline correlation between our SWB index and Facebook use is about three times larger than the experimental estimate of the treatment effect of deactivation (about 0.23 SD compared to 0.09 SD), and the point estimates are highly statistically significantly different. Controlling for basic demographics brings down the non-experimental estimate somewhat, but it remains economically and statistically larger than our experimental estimate. Online Appendix Figure A32 presents the full results for all SWB outcomes.[27] These findings are consistent with reverse causality, for example if people who are lonely or depressed spending more time on Facebook, or with omitted variables, for example if lower socioeconomic status is associated with both heavy use and lower well-being. They could also reflect a difference between the relatively short-term effects measured in our experiment and the longer-term effects picked up in the cross section. However, the lack of a detectable trend in treatment effects on the text message outcomes over the course of our experiment (as noted above and seen in online Appendix Figure A31) points away from this hypothesis.

Subjects' own descriptions in follow-up interviews and free-response questions are consistent with these quantitative findings, while also highlighting substantial heterogeneity in the effects. Many participants described deactivation as an unambiguously positive experience. One said in an interview,

> *I was way less stressed, I wasn't attached to my phone as much as I was before. And I found I didn't really care so much about things that were happening [online] because I was more focused on my own life ... I felt more content. I think I was in a better mood generally. I thought I would miss seeing everyone's day-to-day activities ... I really didn't miss it at all.*

A second wrote, "I realized how much time I was wasting. I now have time for other things. I've been reading books and playing the piano, which I used to do daily until the phone took over."

A third wrote, "I realized I was using it too much and it wasn't making me happy. I hate all of the interactions I had with people in comment sections."

Many others highlighted ways in which deactivation was difficult. One said in an interview,

> *I was shut off from those [online] conversations, or just from being an observer of what people are doing or thinking ... I didn't like it at first at all, I felt very cut off from people that I like ... I didn't like it because I spend a lot of time by myself anyway, I'm kind of an introvert, so I use Facebook in a social aspect in a very big way.*

[26] Specifically, the non-experimental estimates are from the following regression:

$$Y_i^b = \tau \hat{H}_i + \beta \mathbf{X}_i + \epsilon_i, \quad (3)$$

where Y_i^b is participant i's value of some outcome measured in the baseline survey, $\mathbf{X}_i$ is a vector of basic demographic variables (household income, age, and college, male, white, Republican, and Democrat indicators), and $\hat{H}_i$ is baseline average daily Facebook use over the past four weeks (winsorized at 120 minutes per day) divided by the local average treatment effect on average daily Facebook use between midline and endline.

[27] One could also do similar experimental versus non-experimental comparisons for other outcomes, but we have done this only for SWB because SWB is the focus of the non-experimental literature in this area.

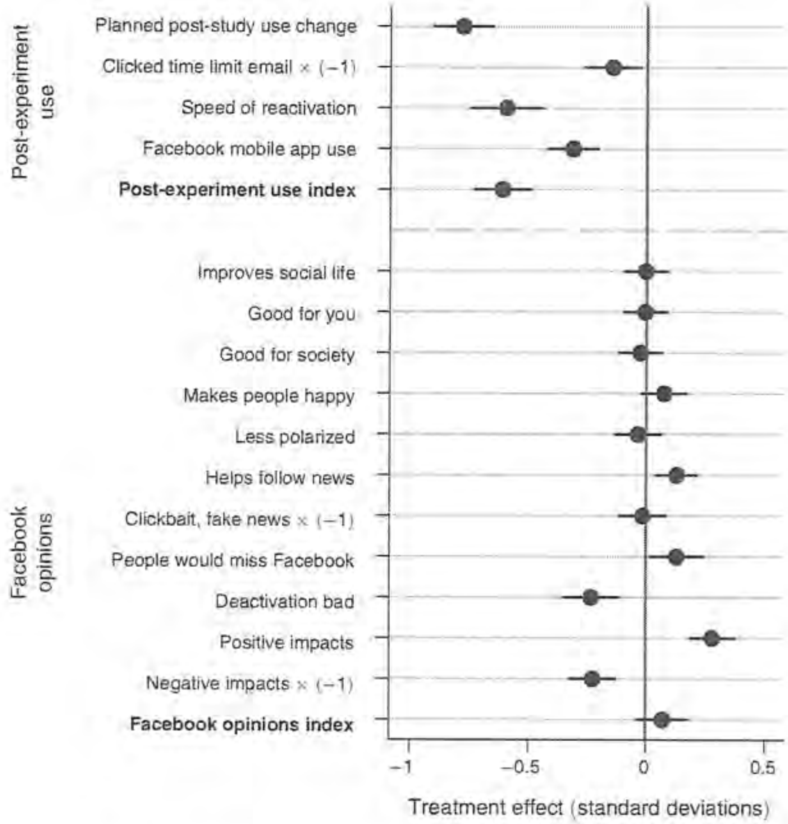


Figure 6. Effects on Post-Experiment Facebook Use and Opinions

Notes: This figure presents local average treatment effects of Facebook deactivation estimated using equation (1). All variables are normalized so that the Control group endline distribution has a standard deviation of 1. Error bars reflect 95 percent confidence intervals. See Section IC for variable definitions.

Others described the difficulty of not being able to post for special events such as family birthdays and not being able to participate in online groups.

Overall, our data suggest that Facebook does indeed have adverse effects on SWB. However, the magnitude of these effects is moderate and may be smaller than correlation studies would suggest, and our qualitative interviews suggest that the average effect likely masks substantial heterogeneity.

D. *Post-Experiment Facebook Use and Opinions*

Figure 6 presents effects of deactivation on post-experiment demand for Facebook as well as participants' subjective opinions about Facebook. These results are closely related to the findings on subjective well-being, as we might expect participants who found deactivation increased their happiness would choose to use Facebook less in the future. They also speak more directly to the popular debate over whether social media are addictive and harmful. If deactivation

reduces post-experiment Facebook use, this is consistent with standard habit formation models such as Becker and Murphy (1988), or with learning models in which experiencing deactivation caused people to learn that they would be better off if they used Facebook less.[28]

Deactivation clearly reduced post-experiment demand for Facebook. These effects are very stark, with by far the largest magnitude of any of our main findings. The effect on reported intentions to use Facebook as of the endline survey is a reduction of 0.78 standard deviations: while the average Control group participant planned to reduce future Facebook use by 22 percent, deactivation caused the Treatment group to plan to reduce Facebook use by an additional 21 percent relative to Control. In our post-endline survey a month after the experiment ended, we measured whether people actually followed through on these intentions, by asking people how much time they had spent on the Facebook mobile app on the average day in the past week. Deactivation reduces this post-endline Facebook mobile app use by 12 minutes per day, or 0.31 standard deviations. This is a 23 percent reduction relative to the Control group mean of 53 minutes per day, lining up almost exactly with the planned reductions reported at endline. However, online Appendix Table A13 shows that the reduction is less than half as large (8 percent of the Control group mean) and not statistically significant (with a t-statistic of -1.16) if we limit the sample to iPhone users who reported their usage as recorded by their Settings app, thereby excluding participants who were reporting personal estimates of their usage.

As a different (and non-self-reported) measure of post-experiment use, we can look at the speed with which people reactivated their Facebook accounts following the 24-hour post-endline period in which both Control and Treatment were deactivated. Figure 7 presents the share of our deactivation checks in which the Treatment and Control groups were deactivated, by day of the experiment.[29] By day 35, one week after the end of the experiment, 11 percent of the Treatment group was still deactivated, compared to 3 percent of the Control group. By day 91, nine weeks after the end of the experiment, 5 percent of the Treatment group was still deactivated, against 2.5 percent of Control. As Figure 6 shows, the local average treatment effect on the speed of reactivation is a highly significant 0.59 standard deviations. Overall, deactivation clearly decreased post-experiment use, reducing the index by 0.61 standard deviations. As introduced above, this is consistent with models of habit formation or learning.

The bottom group of outcomes in Figure 6 supplement the post-experiment use outcomes by measuring participants' qualitative opinions about Facebook. These are re-signed so that more positive means more positive opinions, so agreement with the statement that "Facebook exposes people to clickbait or false news stories" and the length of text about Facebook's negative impacts are both multiplied by (-1).

[28] Online Appendix Figure A33 presents histograms of participants' opinions about Facebook at baseline. People are evenly divided on whether Facebook is good or bad for themselves and for society and whether Facebook makes people more or less happy. Consistent with our results, people tend to think that Facebook helps people to follow the news better and makes people more politically polarized.

[29] There is a slight dip in deactivation rates for the Treatment group seven days after the deactivation period began. This was caused by the fact that some participants failed to turn off a default setting in which Facebook reactivates users' profiles after seven days of deactivation. For technical reasons, our deactivation checking algorithm checked the entire Control group once every few days between midline and endline in order to check the Treatment group four times per day. After endline, we returned to checking all participants approximately once per day.

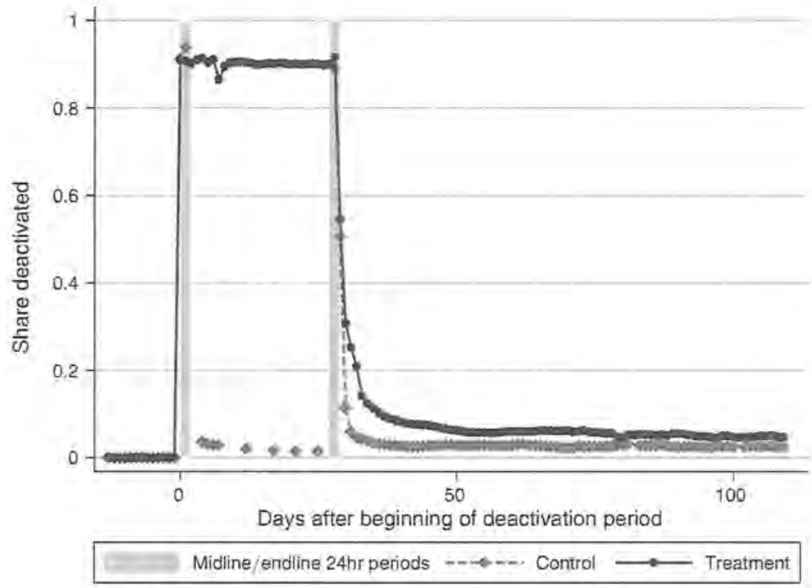


FIGURE 7. PROBABILITY OF BEING DEACTIVATED

Notes: This figure shows the share of the Treatment and Control groups that had their Facebook accounts deactivated, by day of the experiment, for the impact evaluation sample: participants who were willing to accept less than \$102 to deactivate Facebook for the four weeks after midline and were offered $p = \$102$ or $p = \$0$ to do so. The vertical gray areas reflect the 24-hour periods after midline and endline during which both Treatment and Control were instructed to deactivate.

The results are mixed. Deactivation increases the extent to which participants think Facebook helps them follow the news better, and it also makes participants agree more that people would miss Facebook if they stopped using it. On the other hand, participants who deactivated for four weeks instead of 24 hours were more likely to say that their deactivation was good for them.[30] Deactivation increases both the *positive impacts* and *negative impacts* variables, i.e., it makes people write more about both positive and negative aspects of Facebook. Overall, deactivation had no statistically significant effect on the Facebook opinions index.

Figure 8 presents the distributions of Treatment and Control responses to two key questions reflecting opinions about Facebook. Both Treatment and Control tended to agree that "if people spent less time on Facebook, they would soon realize that they don't miss it," but deactivation weakened that view. On this figure, the Treatment group's average response on the scale from -5 to $+5$ was -1.8, while the Control group's average response is -2.0. The right panel shows that both Treatment and Control tended to think that deactivation was good for them, but the Treatment group is more likely to think that their (longer) deactivation was good for them. On this figure, the Treatment group's average response on the scale from

[30] One should be cautious in interpreting this effect, as it could result both from a change of opinion about Facebook and from the difference in length of the deactivation they were evaluating. As we shall see below, the Control group also tends to believe that deactivation was good for them, but the modal answer was 0 (i.e., neither good nor bad), suggesting that many people were indifferent to such a short deactivation.

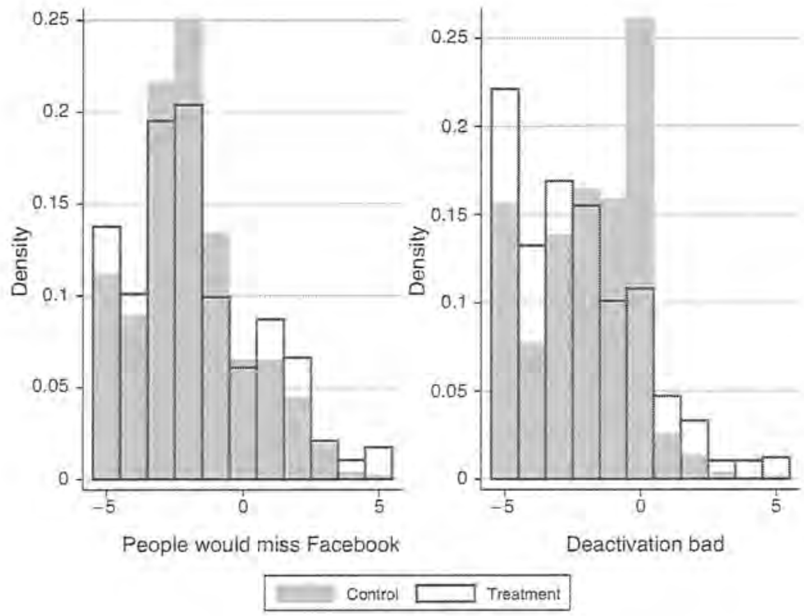


FIGURE 8. KEY OPINIONS ABOUT FACEBOOK IN TREATMENT AND CONTROL

Notes: This figure presents the distribution of responses in Treatment and Control for two key measures of opinions about Facebook. See Section IC for variable definitions.

-5 to $+5$ is -2.3, while the Control group's average response is -1.9. Remarkably, about 80 percent of the Treatment group thought that deactivation was at least somewhat good for them, and the modal response was the strongest possible agreement that deactivation was good (the left-most bar on the histogram). In both panels, the Treatment group has a wider dispersion of responses, with more people strongly agreeing *and* more people strongly disagreeing. This highlights the importance of testing for treatment effect heterogeneity, which we will do in the next section.

To give a richer sense of how deactivation affected Facebook use, the post-endline survey included a free-response question in which we asked people to write how they had changed their Facebook use since participating in the study. We then use standard text analysis tools to determine how the Treatment and Control groups responded differently. Specifically, we processed the text by stemming words to their linguistic roots (for example, "changes," "changing," and "changed" all become "chang"), removing common "stop words" (such as "the" and "that"), and making lists of all one-, two-, three-, and four-word phrases that appeared five or more times in the sample. We then constructed Pearson's χ^2 statistic, which measures the extent of differential usage rates between Treatment and Control; the phrases with the highest χ^2 are especially unbalanced between the two groups. This parallels Gentzkow and Shapiro's (2011) approach to determining which phrases are used more by Republicans versus Democrats, except we determine which phrases are used more by Treatment versus Control.

The two panels of Table 4 present the 20 highest-χ^2 phrases that were more common in Treatment and in Control. The Treatment group was relatively likely

Table 4—Most Common Descriptions of Facebook Use Changes

Phrases used more often by Treatment			Phrases used more often by Control		
Phrase	% Treatment	% Control	Phrase	% Treatment	% Control
Not use facebook anymor	0.90	0	Ha not chang	6.63	16.76
Not spend much time	1.08	0.36	Not chang sinc particip	0	0.99
Spend less time facebook	0.90	0.27	Ha not chang sinc	0.18	1.53
Have not use facebook	0.72	0.18	Chang sinc particip studi	0	0.81
Not use facebook much	0.72	0.18	Way use facebook ha	0.18	1.35
Spend lot less time	0.72	0.27	Usag ha not chang	0	0.72
Use much less	2.87	0.63	Chang way use facebook	0.18	1.26
Definit use facebook	0.54	0.18	Not chang	7.17	18.65
Use facebook lot less	0.54	0.18	Awar much time spend	0	0.63
Use facebook much less	0.54	0.18	Ha not	8.24	19.64
Not use facebook	3.05	1.17	Not much ha chang	0	0.54
Use littl bit less	0.54	0.27	Way use facebook	0.54	2.70
Have not use	1.25	0.18	Not think chang much	0	0.45
Ha not chang use	0.72	0.45	Not chang much use	0	0.45
Use facebook anymor	0.90	0.09	Use facebook slightli less	0	0.45
Think use less	1.61	0.45	More awar much time	0.18	0.99
No ha not chang	0.54	0.36	Chang sinc particip	0	1.08
Use news app	0.72	0.09	Much time spend	0.18	1.53
Still have not	0.90	0.18	Facebook ha not chang	0.72	2.07
Much less	4.84	1.17	Use slightli less	0	0.90

Notes: The post-endline survey included the following question with an open response text box: "How has the way you use Facebook changed, if at all, since participating in this study?" For all responses, we stemmed words, filtered out stop words, then constructed all phrases of length $l = \{1, 2, 3, 4\}$ words. For each phrase p of length l, we calculated the number of occurrences of that phrase in Treatment and Control group responses (f_{plT} and f_{plC}) and the number of occurrences of length-l phrases that are *not* phrase p in Treatment and Control responses ($f_{\sim plT}$ and $f_{\sim plC}$). We then constructed Pearson's χ^2-statistic:

$$\chi^2 = \frac{\left(f_{plT} f_{\sim plC} - f_{plC} f_{\sim plT}\right)^2}{\left(f_{plT} + f_{plC}\right)\left(f_{plT} + f_{\sim plT}\right)\left(f_{plC} + f_{\sim plC}\right)\left(f_{\sim plT} + f_{\sim plC}\right)}.$$

This table presents the 20 phrases with the highest χ^2 that were most commonly written by the Treatment and Control groups. The % Treatment and % Control columns present the share of people in the respective group whose responses included each phrase.

to write that they were using Facebook less or not at all ("use much less," "not use facebook anymor," "stop use facebook") or more judiciously: the phrase "use news app" is mostly from people saying that they have switched to getting news from their phone's news app instead of Facebook. By contrast, while a few of the Control group's most common phrases indicate lower use (variants of "more aware much time spend" and "use facebook slightli less"), the great majority of their relatively common phrases indicate that their Facebook use has not changed.

To more deeply understand the ways in which deactivation changed people's relationship to Facebook, we partnered with a team of qualitative researchers who analyzed our survey data and additional participant interviews (Baym, Wagman, and Persaud forthcoming). They find that many participants emphasized that their time off of Facebook led them to use the platform more "consciously," aligning their behavior with their desired use. For example, some participants discussed avoiding their news feed and only looking at their Facebook groups, while others removed the Facebook app from their phones and only accessed the site using their computers.

E. *Heterogeneous Treatment Effects*

Individual Moderators.—In our pre-analysis plan, we specified that we would present separate estimates for subgroups defined by four primary moderators. Figure 9 presents those estimates. The top panel presents estimates for *heavy users* versus *light users*: that is, people whose baseline reported Facebook use was above versus below median. There is no consistent evidence that the effects are different for people who report being heavier users, perhaps because Facebook use is measured with noise.

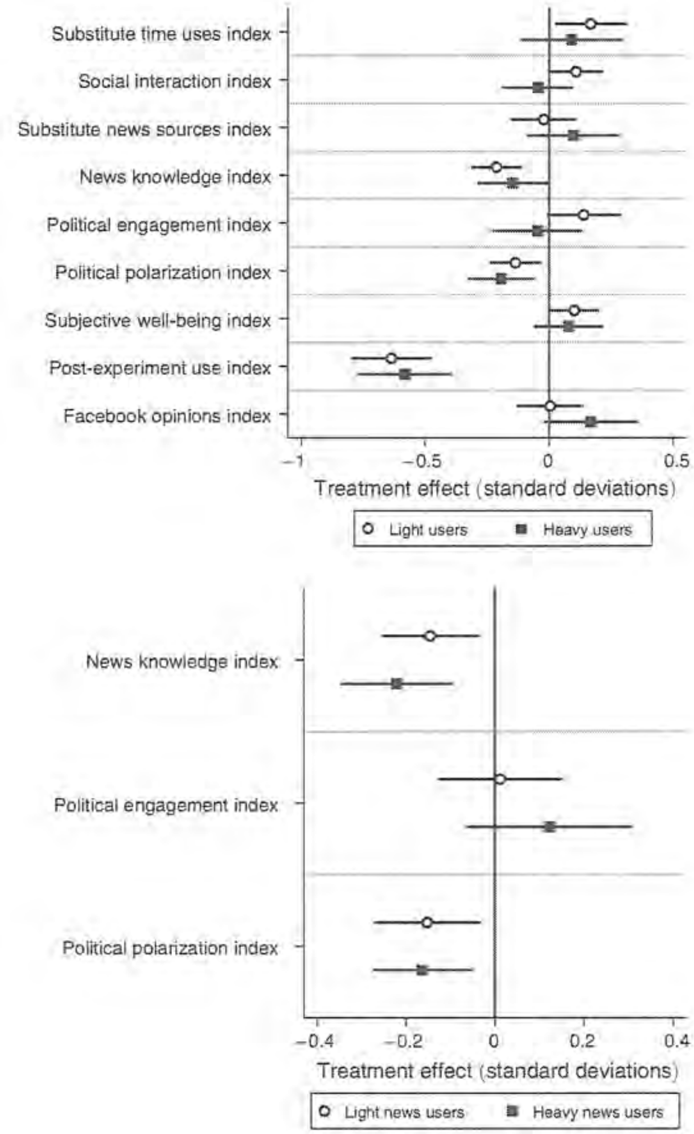
The second panel presents estimates for *heavy news users* versus *light news users*: that is, those who get news from Facebook fairly often or very often versus never, hardly ever, or sometimes. As one might expect, the estimated effects for news knowledge are larger for people who get more news from Facebook, but this difference is not statistically significant. The pre-analysis plan specified that we would limit these tests to only the news and political outcomes in Section IVB.

The third panel presents separate estimates for *active users* versus *passive users*. We measure this using two questions: share of active versus passive browsing using a question based on the Passive and Active Facebook Use Measure (Gerson, Plagnol, and Corr 2017), and "what share of your time on Facebook do you spend interacting one-on-one with people you care about." Active versus passive users are defined as having above- versus below-median sum of their two responses to these questions. This moderator is of interest because of a set of papers cited in the introduction suggesting that passive Facebook use can be harmful to subjective well-being, while active use might be neutral or beneficial. Perhaps surprisingly, we see no differences in the effects of deactivation on the subjective well-being index. The pre-analysis plan specified that we would limit these tests to the four families reported in the figure.

Finally, the fourth panel presents separate estimates of effects on subjective well-being text message surveys for text messages sent during the time of day when the respondent reported using Facebook the most. We see no clear differences in the effects on subjective well-being.

The pre-analysis plan also specified two secondary moderators: age (for all outcomes) and political party (limited to the news and political outcomes). We considered these secondary because we did not have a strong prior that we would be able to detect heterogeneous effects. Online Appendix Figure A9 presents estimates of effects on these outcomes. There are no systematic patterns.

Online Appendix Figure A9 also includes heterogeneity by above- versus below-median valuation of Facebook. While we added this moderator only after the pre-analysis plan was submitted, it is important because our impact evaluation sample only includes participants with WTA less than \$102. Under the assumption that marginal treatment effects are monotonic in WTA, treatment effect heterogeneity within our impact evaluation sample would be informative about treatment effects for the full population. The effects for above- versus below-median WTA differ statistically for only one index: the effects on political polarization are driven by above-median WTA participants. The above-median WTA point estimate is larger and statistically indistinguishable for two indices, smaller and statistically



(*Continued*)

FIGURE 9. HETEROGENEOUS TREATMENT EFFECTS

indistinguishable for four indices, and opposite-signed for the final index. This provides some support for the view that effect sizes would not be systematically different in the full Facebook user population including users with higher valuations.

Online Appendix Figure A9 presents one additional test of external validity that was suggested by a referee after the pre-analysis plan was submitted. We construct sample weights that match the impact evaluation sample to the observable characteristics of Facebook users in Table 2. Online Appendix Figure A9 shows that participants with below- versus above-median sample weights, that is, the types of

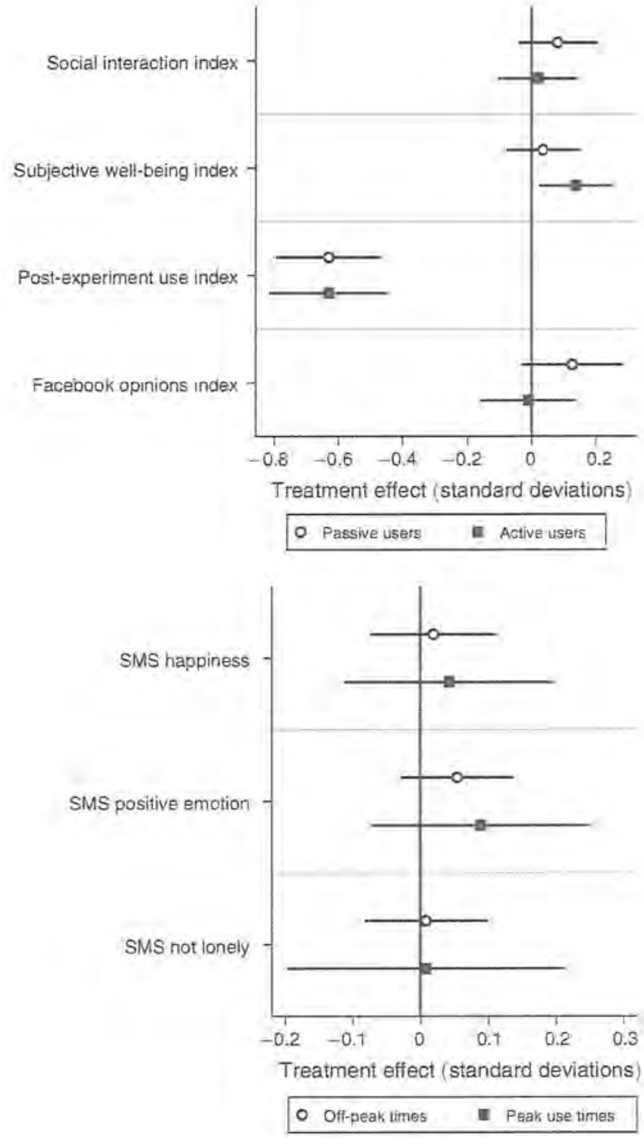


Figure 9. Heterogeneous Treatment Effects (Continued)

Notes: This figure presents local average treatment effects of Facebook deactivation estimated using equation (1), for subgroups defined by the primary moderators in our pre-analysis plan. All variables are normalized so that the Control group endline distribution has a standard deviation of 1. Error bars reflect 95 percent confidence intervals. See Section IC for variable definitions.

people who were especially likely versus unlikely to participate in the study, do not have systematically different treatment effects. This provides some further support for the view that effect sizes would be similar in the full Facebook user population.

Online Appendix F presents heterogeneous treatment effects on each individual outcome.

All Possible Moderators.—Many factors other than the specific variables we specified above might moderate treatment effects of Facebook deactivation. To search for additional possible moderators, we test whether any of the demographics or outcome variable indices collected at baseline might moderate treatment effects on the key outcomes of interest. We consider six outcomes: the latter five indices (news knowledge, political polarization, subjective well-being, post-experiment use, and Facebook opinions) plus the variable *Deactivation bad*, which we add because of the heterogeneity displayed in Figure 8. We consider 13 potential moderators: all 6 demographic variables listed in Table 2 (income, years of education, gender, race, age, and political party affiliation, which is on a seven-point scale from strongly Democratic to strongly Republican) and the baseline values of all 7 relevant indices.[31] We normalize each potential moderator to have a standard deviation of 1, and we denote normalized moderator k by X_i^k.

For all outcomes other than *Deactivation bad*, we estimate the following modified version of equation (1):

$$Y_i = \tau D_i + \alpha^k D_i X_i^k + \zeta X_i^k + \rho \mathbf{Y}_i^b + \nu_s + \varepsilon_i, \quad (4)$$

instrumenting for D_i and $D_i X_i^k$ with T_i and $T_i X_i^k$. For *Deactivation bad*, we simply estimate $Y_i = \alpha^k X_i^k + \varepsilon_i$ in the Treatment group only; this identifies what types of people in the Treatment group thought that deactivation was particularly good or bad. In total, we carry out 78 tests in 78 separate regressions: 13 potential moderators for each of the 6 outcomes.

There are many ways to estimate heterogeneous treatment effects, including causal forests (Athey, Tibshirani, and Wagner 2019) and lasso procedures. We chose this approach because it delivers easily interpretable estimates.

Figure 10 presents the interaction coefficients $\hat{\alpha}^k$ and 95 percent confidence intervals for each of the six outcomes. To keep the figures concise, we plot only the five moderators with the largest absolute values of $\hat{\alpha}^k$, so there are another eight smaller unreported $\hat{\alpha}^k$ coefficients for each outcome.

We highlight three key results. First, deactivation may reduce polarization more (i.e., Facebook use may increase polarization more) for older people, white people, and men. Second, Facebook deactivation has less positive effect on subjective well-being for people who have more offline social interactions and are already more happy at baseline. This suggests that Facebook use may have the unfortunate effect of reducing SWB more for people with greater social and psychological need. In our sample, these "higher-need" people also use Facebook more heavily. Third, people may have some intuition about whether they will like deactivation: people with more positive baseline opinions about Facebook are less likely to decrease their post-experiment use and less likely to think that deactivation was good for them.

[31] There are originally nine indices. We exclude the baseline substitute time uses index because it is not easily interpretable, and we exclude the baseline post-experiment use index because this only includes *Facebook mobile app use*.

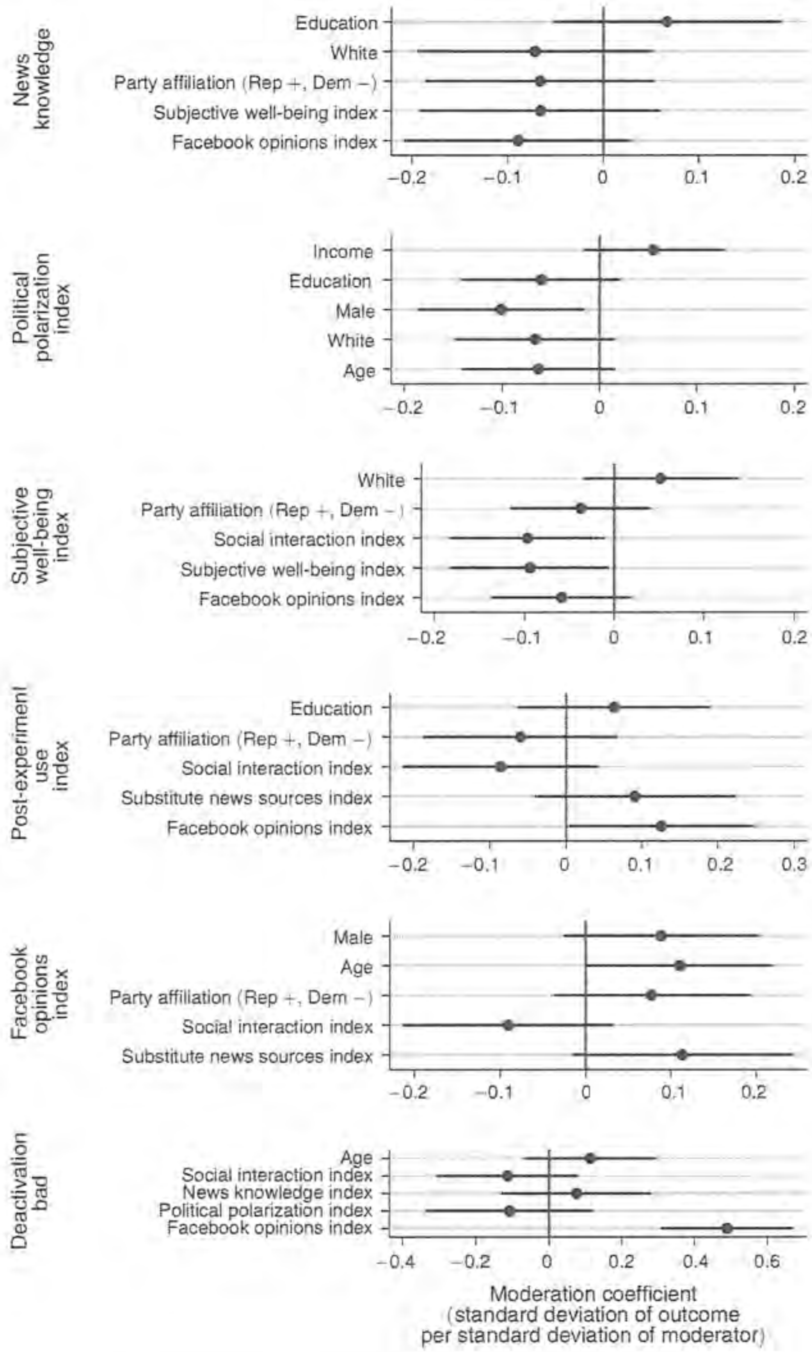


FIGURE 10. HETEROGENEOUS TREATMENT EFFECTS FOR ALL MODERATORS

Notes: This figure presents the moderators of local average treatment effects of Facebook deactivation estimated using equation (4). For each of the six outcomes, we present the five moderators with the largest moderation coefficients $\hat{\alpha}^{k}$. All outcome variables are normalized so that the Control group endline distribution has a standard deviation of 1, and all moderators are also normalized to have a standard deviation of 1. Error bars reflect 95 percent confidence intervals. See Section IC for variable definitions.

TABLE 5—PERCEIVED RESEARCHER AGENDA IN TREATMENT AND CONTROL

Variable	Treatment mean/SD (1)	Control mean/SD (2)	t-test p-value (1) − (2)
I don't think they had a particular agenda	0.43 (0.49)	0.44 (0.50)	0.59
Yes, wanted to show that Facebook is good for people	0.03 (0.18)	0.04 (0.19)	0.79
Yes, wanted to show that Facebook is bad for people	0.35 (0.48)	0.35 (0.48)	0.79
I am not sure	0.19 (0.39)	0.18 (0.38)	0.62
Observations	573	1,064	

Notes: The endline survey asked, "Do you think the researchers in this study had an agenda?" Columns 1 and 2 present the share of the Treatment and Control groups who gave each possible response. Column 3 presents p-values of tests of differences in means between the two groups.

F. *Experimenter Demand Effects*

Most of our outcomes are self-reported, and it would have been difficult to further conceal the intent of the randomized experiment. This raises the possibility of experimenter demand effects, i.e., that survey responses depend on what participants think the researchers want them to say. To test for demand effects, the endline survey asked, "Do you think the researchers in this study had an agenda?" Table 5 presents the possible responses and shares by treatment group.

For demand effects to arise, participants must believe that the researchers want a particular pattern of responses. Table 5 shows that 62 percent of both Treatment and Control groups thought we had no particular agenda or were not sure. This suggests that demand effects would not arise for a solid majority of our sample. However, demand effects could arise for the remaining 38 percent.

For experimenter demand effects to bias our treatment effects, either (i) the Treatment and Control groups must have different beliefs about what the researchers want, or (ii) participants must sense what treatment group they are in and change their answers to generate the treatment effect that they think the researchers want (or don't want). Table 5 shows that possibility (i) is not true: perceived researcher agenda is closely balanced between Treatment and Control. To test for possibility (ii), we can estimate treatment effects separately for the subsample that thought that we "wanted to show that Facebook is bad for people" versus all other participants. If (ii) is true, then our results should be different in these two subsamples. Online Appendix Figure A36 shows that this is not the case: the effects on outcome indices that look "good" or "bad" for Facebook (e.g., news knowledge, political polarization, subjective well-being, and post-experiment use) are not statistically different, and there is no pattern of point estimates to suggest that the results are generally more "good" or "bad" in one of the two subsamples.

Of course, these tests are only suggestive. But combined with the fact that the non-self-reported outcomes paint a similar picture to the self-reports, these tests suggest that demand effects are unlikely to be a major source of bias in our results.

V. Measuring the Consumer Surplus from Facebook

Quantifying the economic gains from free online services such as search and media is particularly important given that these services represent an increasingly large share of the global economy. This measurement has been particularly challenging because the lack of price variation (or any price at all) makes it impossible to use standard demand estimation to measure consumer surplus.[32] In this section, we present two back-of-the-envelope consumer surplus calculations. First, we employ the standard assumption that willingness-to-accept identifies consumer surplus. Second, we adjust consumer surplus to account for the possibility that deactivation might help people learn their true valuation of Facebook. This adjustment highlights the challenges in using willingness-to-accept as a measure of consumer welfare.

A. *Standard Consumer Surplus Estimate*

In a standard model, willingness-to-accept to abstain from Facebook equals consumer surplus. Figure 11 presents the histogram of WTA to deactivate Facebook for the four weeks after midline instead of only the 24 hours after midline. The median is $100, and almost 20 percent had valuations greater than $500. After winsorizing valuations at $1,000, the mean is $203. After reweighting the sample to match the observable characteristics of Facebook users in Table 2, the median is still $100, and the winsorized mean is $180. Multiplying the mean by the estimated 172 million US Facebook users would imply that 27 days of Facebook generates $31 billion of consumer surplus.

Our sample's WTA for Facebook abstention is larger than in most other studies, but not all. In an online panel weighted for national representativeness, Brynjolfsson, Eggers, and Gannamaneni (2018) estimates that the mean WTA to not use Facebook for one month is $48, and that the median WTA to hypothetically stop using social media for one year was $205 in 2016 and $322 in 2017. In their sample of European college students, Brynjolfsson, Eggers, and Gannamaneni (2018) finds a median WTA of $175 for one month.[33] In samples of college students, residents of a college town, and Amazon MTurk workers, Corrigan et al. (2018) estimates that the mean annualized WTA to deactivate Facebook ranges from $1,139 to $1,921, depending on the sample and the length of deactivation. In a sample of college students, Mosquera et al. (2018) estimates that the median (mean) WTA to not use Facebook for one week is $15 ($25). In an unincentivized (stated preference) survey of MTurk workers, Sunstein (forthcoming) found a $1 per month median willingness-to-pay for Facebook and a $59 per month median willingness-to-accept to not use Facebook.

There are many caveats to using this type of stylized calculation to approximate the consumer surplus from Facebook. First, we (and Corrigan et al.) required participants to deactivate their Facebook accounts instead of simply abstaining from logging in. For people who planned to avoid using other apps with Facebook logins

[32] As mentioned in the introduction, see Brynjolfsson and Saunders (2009); Byrne, Fernald, and Reinsdorf (2016); Nakamura, Samuels, and Soloveichik (2016); Brynjolfsson, Rock, and Syverson (2019); and Syverson (2017).

[33] Online Appendix Figure A37 compares our demand curve to the Brynjolfsson, Eggers, and Gannamaneni (2018) demand curves.

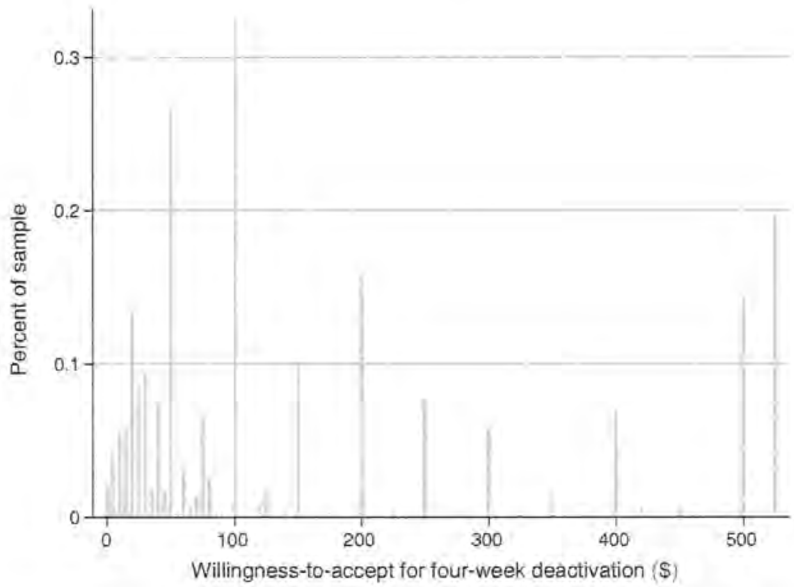


FIGURE 11. DISTRIBUTION OF WILLINGNESS-TO-ACCEPT TO DEACTIVATE FACEBOOK AFTER MIDLINE

Notes: This figure presents the distribution of willingness-to-accept to deactivate Facebook between midline and endline. All responses above $525 are plotted at $525.

in order to avoid reactivating their Facebook accounts, WTA overstates the value of Facebook access. Second, participants must believe the experimenter will in fact enforce deactivation; WTA could naturally be lower for a partially enforced or unenforced deactivation compared to an enforced deactivation. In some other studies, the method of enforcement was either not made clear ex ante, or enforcement was not fully carried out ex post.[34] Third, any survey sample is unlikely to be representative of the Facebook user population on both observable and unobservable characteristics. For example, we screened out people who reported using Facebook 15 minutes or less per day, and while we reweight the average WTAs to match the average observables of Facebook users (including average daily usage), this reweighting may implicitly overstate the WTA of people who don't use Facebook very much. Fourth, we (and all other existing studies) estimate people's Facebook valuations holding their networks fixed. Due to network externalities, valuations could be quite different if participants' friends and family also deactivated. Fifth, one should be careful in annualizing these estimates or comparing WTAs for different durations of abstention, as our study and several others find that the average per-day valuation varies with the duration. Sixth, as we will see, in practice people's WTA may not be closely held and could be easily anchored or manipulated, even in incentive

[34] Mosquera et al. told participants that they would "require" that they "not use their Facebook accounts" but did not give additional details. Brynjolfsson et al.'s WTA elicitation stated that the experimenters "will randomly pick 1 out of every 200 respondents and her/his selection will be fulfilled," and that they could enforce deactivation by observing subjects' time of last login, "given your permission." In practice, the deactivation was mostly not enforced: of the ten subjects randomly selected for enforcement, one gave permission.

compatible elicitations such as ours. Finally, this calculation fails to speak to the possibility that people misperceive Facebook's value. We turn to that issue now.

B. *How Deactivation Affects Valuations*

It is often argued that social media users do not correctly perceive the ways in which social media could be addictive or make them unhappy. If this is the case, people's willingness-to-accept to abstain from Facebook would overstate "true" consumer surplus. For example, Alter (2018), Newport (2019), many popular media articles,[35] and organizations such as the Center for Humane Technology and Time to Log Off argue that Facebook and other digital technologies can be harmful and addictive. The Time to Log Off website argues that "everyone is spending too much time on their screens" and runs "digital detox campaigns." Sagioglu and Greitemeyer (2014) documents an "affective forecasting error": people predicted that spending 20 minutes on Facebook would make them feel better, but a treatment group randomly assigned to 20 minutes of Facebook browsing actually reported feeling worse.

Some of our results are also consistent with this argument. In the baseline survey, two-thirds of people agreed at least somewhat that "if people spent less time on Facebook, they would soon realize that they don't miss it." As reported earlier, about 80 percent of the Treatment group thought that deactivation was good for them, and both qualitative and quantitative data suggest that deactivation caused people to rethink and reoptimize their use.

The core of this argument is that people's social media use does not maximize their utility, and a "digital detox" might help them align social media demand with their own best interests. This idea is related to several existing economic models. In a model of projection bias (Loewenstein, O'Donoghue, and Rabin 2003), people might not correctly perceive that social media are habit forming or that their preferences might otherwise change after a "digital detox." In an experience good model, a "digital detox" might help consumers to learn their valuation of social media relative to other uses of time. Of course, both of these mechanisms could also affect demand after a period of deactivation, so it is not clear whether the WTA before deactivation or after deactivation is more normatively relevant.

To provide evidence on these issues, we elicited WTA at three points, as described earlier. First, on the midline survey, we elicited WTA to deactivate Facebook in "weeks 1–4" (the four weeks after midline). We call this WTA w_1. Second, just after telling people their BDM offer price on the midline survey, and thus whether they were expected to deactivate in weeks 1–4, we elicited WTA to deactivate in "weeks 5–8" (the four weeks after endline). We call this $w_{2,1}$. Third, on the endline survey, we elicited WTA to deactivate in weeks 5–8, after the Treatment group had experienced deactivation in weeks 1–4, but the Control group had not. We call this $w_{2,2}$.

[35] For example: Chris Ciaccia, "Facebook, Cocaine, Opioids: How Addictive Is the Social Network?" *Fox News*, December 29, 2017, https://www.foxnews.com/tech/facebook-cocaine-opioids-how-addictive-is-the-social-network; Will Oremus, "Addiction for Fun and Profit." *Slate*, November 10, 2017, https://slate.com/technology/2017/11/facebook-was-designed-to-be-addictive-does-that-make-it-evil.html.

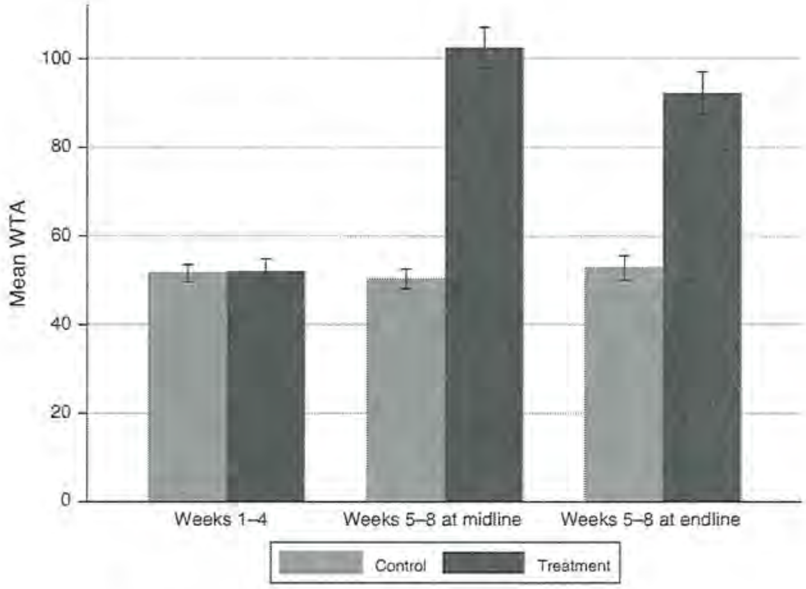


FIGURE 12. AVERAGE VALUATION OF FACEBOOK IN TREATMENT AND CONTROL

Notes: This figure presents the mean willingness-to-accept (WTA) to deactivate Facebook in Treatment and Control, for the impact evaluation sample: participants who were willing to accept less than \$102 to deactivate Facebook for the four weeks after midline and were offered $p = \$102$ or $p = \$0$ to do so. The first pair of bars is the mean WTA for deactivation in weeks 1–4, the four weeks after the midline survey. The second pair of bars is mean WTA for deactivation in weeks 5–8, the four weeks after the endline survey, as elicited in the midline survey. The third pair of bars is mean WTA for deactivation in weeks 5–8, as elicited in the endline survey.

The Control group's change in WTA for weeks 5–8, $\Delta w_2 := w_{2,2} - w_{2,1}$, captures any unpredicted time effect. The Treatment group's WTA change Δw_2 reflects both the time effect and the unexpected change in valuation caused by deactivation. If the time effect is the same in both groups, then the difference-in-differences measures the effect of deactivation on valuations due to projection bias, learning, and similar mechanisms.

Figure 12 presents the average of WTA in Treatment and Control of w_1, $w_{2,1}$, and $w_{2,2}$. Recall that the impact evaluation sample includes only people with $w_1 < \$102$, so these averages are less than the unconditional means discussed above and presented in Figure 11. Because of outliers in the WTAs for weeks 5–8, we must winsorize WTA. We winsorize at \$170 for this figure and our primary regression estimates, as this is the upper bound of the distribution of BDM offers that we actually made for deactivation.

The Treatment group's valuation for weeks 5–8 jumps substantially relative to its valuation for weeks 1–4, while the Control group's valuation for weeks 5–8 does not. We used open-answer questions in the post-endline survey and qualitative interviews to understand this change. Some of the large gap may be due to costs of deactivation being convex in the length of deactivation: some people in the Treatment group wrote that they were much less comfortable deactivating for eight weeks instead of four, as they would have to make much more extensive arrangements to communicate with friends, coworkers, and schoolmates during a longer deactivation. However, participants' open-answer responses suggest that the

Treatment group's WTA increase is also affected by anchoring on the $102 BDM offer that was revealed after the elicitation of w_1 but before the elicitation of $w_{2,1}$. Such anchoring is consistent with prior results showing that valuations elicited using the BDM method can be affected by suggested prices or other anchors (Bohm, Lindén, and Sonnegård 1997; Mazar, Kőszegi, and Ariely 2014). Thus, we do not believe this increase is relevant for a consumer welfare calculation, and we do not draw any substantive conclusion from it.

Figure 12 also illustrates Δw_2, the change in valuation of weeks 5–8 between midline and endline. The Control group's valuation increases, reflecting an unpredicted time effect. In open-answer questions, some people wrote that they were less willing to deactivate during the Thanksgiving holiday, and they may not have foreseen this as of the midline survey on October 11. By contrast, the Treatment group's valuation for weeks 5–8 decreases. Thus, the difference-in-differences Δw_2 is negative.

We can estimate the difference-in-differences using the following regression:

$$\Delta w_{2,i} = \gamma D_i + \rho w_{1,i} + \nu_s + \varepsilon_i, \tag{5}$$

instrumenting for D_i with T_i. Table 6 presents results, winsorizing all WTAs at $170 in column 1 and at $1,000 in column 2. Relative to the Control group, the Treatment group reduced its post-endline valuation by $14 to $18, or about 14 percent of the Treatment group's average $w_{2,1}$. This suggests that deactivation eliminated projection bias or facilitated learning that reduced demand for Facebook by 14 percent. In turn, this suggests that the traditional estimates might somewhat overstate consumer surplus.

This result is consistent with our finding in Section IVD that deactivation reduced post-experiment Facebook use. However, because the WTA update Δw_2 is unexpected, it suggests that the results from Section IVD may not be entirely explained by a "rational" habit formation model such as Becker and Murphy (1988), in which people foresee how consumption affects future marginal utility. Instead, these results suggest that at least some of the reduced Facebook demand caused by deactivation is driven by unexpected factors such as projection bias and learning.

One caveat is that the anchoring effect described above could affect our estimate of γ. If anchoring has the same effects on $w_{2,1}$ and $w_{2,2}$ in the Treatment group, then Δw_2 is unaffected, and our estimate of γ is unbiased. If the anchoring effects decay between midline and endline, this would bias $\hat{\gamma}$ away from zero, meaning that the true γ would be less than our estimate.[36] This would further strengthen our result that the valuation update caused by deactivation equals only a small share of valuations.

One interpretation of these results is that they reinforce the standard model calculation that Facebook generates many billions of dollars in consumer surplus. Another interpretation is that they further highlight why standard consumer surplus calculations based on elicited valuations can be problematic.

[36] An alternative experimental design choice we considered was to elicit $w_{2,1}$ *before* revealing the weeks 1–4 offer price, separately for the case in which the participant would be paid to deactivate for weeks 1–4 and the case in which the participant would not be paid to deactivate. In this case, however, any anchoring effect would have appeared on $w_{2,2}$ but not $w_{2,1}$, generating an unambiguous spurious treatment effect on Δw_2.

TABLE 6—CHANGE IN FACEBOOK VALUATION AFTER DEACTIVATION

	(1)	(2)
Share of time deactivated	−14.36	−18.22
	(2.60)	(7.73)
Observations	1,634	1,634
Winsorized maximum WTA	170	1,000
Treatment mean weeks 5–8 WTA at midline	103	135

Notes: This table presents estimates of equation (5). The dependent variable is the change in WTA for post-endline deactivation measured at endline versus midline. Standard errors are in parentheses.

VI. Conclusion

Our results leave little doubt that Facebook provides large benefits for its users. Even after a four-week "detox," our participants spent substantial time on Facebook every day and needed to be paid large amounts of money to give up Facebook. Our results on news consumption and knowledge suggest that Facebook is an important source of news and information. Our participants' answers in free response questions and follow-up interviews make clear the diverse ways in which Facebook can improve people's lives, whether as a source of entertainment, a means to organize a charity or an activist group, or a vital social lifeline for those who are otherwise isolated. Any discussion of social media's downsides should not obscure the basic fact that it fulfills deep and widespread needs.

Notwithstanding, our results also make clear that the downsides are real. We find that four weeks without Facebook improves subjective well-being and substantially reduces post-experiment demand, suggesting that forces such as addiction and projection bias may cause people to use Facebook more than they otherwise would. We find that while deactivation makes people less informed, it also makes them less polarized by at least some measures, consistent with the concern that social media have played some role in the recent rise of polarization in the United States. The estimated magnitudes imply that these negative effects are large enough to be real concerns, but also smaller in many cases than what one might have expected given prior research and popular discussion.

The trajectory of views on social media, with early optimism about great benefits giving way to alarm about possible harms, is a familiar one. Innovations from novels to TV to nuclear energy have had similar trajectories. Along with the important existing work by other researchers, we hope that our analysis can help move the discussion from simplistic caricatures to hard evidence, and provide a sober assessment of the way a new technology affects both individual people and larger social institutions.

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Article

The Association of Social Media Use and Eating Behaviour of Belgian Adolesce ... prexia Nervosa—A Qua...

DIAGNOSED ED'S

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Ab... n adolescents' lives, presenting both op... ies like eating disorders, prevalent in thi... mployed semi-structured interviews wi... g disorders. Interviews covered seven pr... lysis. Results: Participants identified fou... pretation, behavioural adaptation, and evolving perspectives during recovery. They highlighted social media's role in exacerbating body dissatisfaction and altering behaviours related to eating disorders. Conclusions: This research underscores the critical need for awareness and guidance in adolescents' social media use to mitigate negative impacts, emphasizing the potential link between exposure to specific content and cognitive-behavioural changes in those with eating disorders. Further investigation is warranted to deepen our comprehension of these dynamics.

Keywords: selective content; biased interpretation; behavioural adaptation; recovery process; body dissatisfaction; comparison

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1. Introduction

A substantial majority (97%) of adolescents in industrialized nations engage with social media regularly, signifying its integral role in their daily lives and broader societal dynamics [1]. Over the last few years, traditional media have been increasingly replaced by social media, which offer both active and passive use. These platforms are continuously accessible and provide a vast array of information, entertainment, social interaction, and marketing opportunities [2]. Consequently, social media significantly influence adolescents' social and emotional development [1].

Children and adolescents are engaging with social media at younger ages as mobile device ownership becomes more common, leading to the formation of their social media portfolios at a considerably younger age [2]. Gender differences in social media use are evident: girls predominantly use platforms like Instagram and Tumblr, whereas boys prefer Facebook. Girls tend to maintain private accounts and frequently post personal content, while boys are more likely to have public accounts and share memes and possessions. These gender-based differences in social media use are associated with varied impacts on boys and girls [3].

The increased use of social media among adolescents exposes them to potential risks, including pornography, violence, and cyberbullying, affecting approximately 15% of this

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Article

The Association of Social Media Use and Eating Behaviour of Belgian Adolescent Girls Diagnosed with Anorexia Nervosa—A Qualitative Approach

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Abstract: Background: Social media have become integral in adolescents' lives, presenting both opportunities and risks, especially concerning psychiatric issues like eating disorders, prevalent in this vulnerable age group. Methods: This qualitative study employed semi-structured interviews with seven adolescent girls (aged 15–17) diagnosed with eating disorders. Interviews covered seven predefined topics, recorded and transcribed for thematic analysis. Results: Participants identified four key themes: exposure to selective content, biased interpretation, behavioural adaptation, and evolving perspectives during recovery. They highlighted social media's role in exacerbating body dissatisfaction and altering behaviours related to eating disorders. Conclusions: This research underscores the critical need for awareness and guidance in adolescents' social media use to mitigate negative impacts, emphasizing the potential link between exposure to specific content and cognitive-behavioural changes in those with eating disorders. Further investigation is warranted to deepen our comprehension of these dynamics.

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The increased use of social media among adolescents exposes them to potential risks, including pornography, violence, and cyberbullying, affecting approximately 15% of this

population. These exposures have been linked to depression, anxiety, and lowered self-esteem. Conversely, positive use of social media can enhance mental well-being by strengthening peer relationships, social skills, and support networks, thereby reducing stress [4]. Adolescents often perceive these negative consequences as more impactful on others than on themselves, a phenomenon known as the 'personal fable', influenced by their developmental stage [1].

The prevalence of eating disorders has increased significantly, with a 12.5% rise since 1990, resulting in a lifetime prevalence of 13% [5]. Anorexia nervosa (AN), bulimia nervosa (BN), and binge eating disorder (BED) are now among the most diagnosed eating disorders, with AN being particularly prevalent in clinical settings. Adolescent girls are the most susceptible to eating disorders, with a lifetime prevalence of 4% for developing AN [6–8]. AN is characterized by significant underweight, fear of gaining weight, and a disturbed self-image [6].

Previous research suggests a link between social media use and the development of eating disorders. Network analysis of studies on body image reveals that exposure to 'idealized body appearance' images on social media is a significant factor [9]. 'Fitspiration', a social media trend promoting a healthy lifestyle, has varied effects. Studies show that young women exposed to fitspiration on Instagram often internalize the 'thin ideal', leading to increased body dissatisfaction [3,10–12]. Similarly, TikTok users exposed to such content experience higher body dissatisfaction and reduced self-esteem due to frequent comparisons [13–15]. Body dissatisfaction is a well-established precursor to eating disorders [16–19]. This suggests that social media may contribute to eating disorders by fostering body dissatisfaction.

Despite growing awareness of social media's impact on mental health, most studies have focused on adolescents or adults without pre-existing mental illnesses. There is a lack of research on the influence of social media on individuals diagnosed with eating disorders. This study aims to explore through qualitative semi-structured interviews whether adolescents with eating disorders perceive social media as influencing their illness.

2. Materials and Methods

2.1. Research Design

This study employed a qualitative approach utilizing semi-structured interviews to understand participants' perspectives comprehensively. Semi-structured interviews facilitate the flexibility for detailed exploration of specific viewpoints, allowing for a nuanced understanding of individual experiences. Given the emphasis on personal experiences, a qualitative methodology was chosen over a quantitative survey.

2.2. Design and Validation of the Interview Guide

The development of the interview guide was based on an extensive review of existing literature on eating disorders and their correlation with social media. Multiple medical databases were queried to gather publications concerning the impact of social media on adolescents, biological, psychological, and social changes during adolescence, comprehensive insights into eating disorders, and the current understanding of the interplay between eating disorders and social media. This literature review aimed to establish a solid theoretical framework for the research. Drawing from this theoretical foundation, a structured interview guide was formulated, comprising approximately thirty questions categorized into seven main domains: general social media use, positive and negative outcomes of social media engagement, exposure to specific content on social media platforms, social interactions facilitated by social media, influence of social media on eating behaviours and eating disorders, and social media platforms dedicated to eating disorders. The interview guide followed a gradual approach, initially exploring participants' general social media habits before delving into the connection between their eating disorders and social media. Open-ended questions allowed participants to offer personal interpretations and insights.

2.3. Study Settings and Participants

Participants were recruited from the UZ Leuven paediatrics department by staff members. Inclusion criteria encompassed female adolescents aged 12 to 17 diagnosed with anorexia nervosa (DSM V, restrictive type). We restricted our sample to female participants to limit divergence. The time to diagnosis of AN was not utilized as inclusion or exclusion criteria in this study. The paediatricians assessed the candidates' eligibility for participation. Individuals for whom participation was deemed excessively challenging (due to clinical or psychological concerns) were excluded.

2.4. Data Collection/Interview Process

Following invitation from clinical staff, potential participants received detailed information about the research via a letter to enable informed decision making. Researchers contacted interested candidates, discussing the informed consent process thoroughly before each interview. Participation was voluntary and non-binding, ensuring the freedom to withdraw at any point without repercussions. Written informed consent was obtained from the parents due to participants' minor status, while participants provided verbal assent. Interviews were conducted via live video calls on Teams, with audio recordings obtained with participant consent for transcription purposes. Recordings were stored anonymously and deleted after transcription. Each interview lasted approximately 90 min, followed by an opportunity for participants to address any queries or share reflections on the process. Researchers remained available for further questions or support.

2.5. Data Analysis

Manual transcription of interviews was followed by coding procedures. "Open coding" involved summarization and concept construction through labelling by researchers, with regular meetings to reconcile discrepancies and establish common labels. Subsequently, a "preliminary coding framework" was developed based on these summaries. "Axial coding" introduced overarching categories applicable across all interviews, while "selective coding" finalized the inclusion or exclusion of data.

2.6. Ethical Considerations

The research adhered to the ethical principles endorsed by the Research Ethics Committee UZ/KU Leuven (MP024076), aligning with ICH-GCP standards, Helsinki Declaration, and relevant laws. Informed consent highlighted voluntary and anonymous participation, with participants being informed about audio recordings and their eventual deletion. No identifiable information was collected, and ethical considerations included offering access to psychologists if needed, with researchers available for queries.

3. Results

3.1. Demographics

Seven Caucasian adolescent girls aged 15 to 17, diagnosed with restrictive anorexia nervosa, participated in the study. The average age of the participants was 15 years and 10 months, with an average eating disorder duration of 1 year and 6 months at the time of the interview. Initial BMI at onset ranged from 11.6 to 17.6, with a mean of 15.1. At the time of the interviews, BMI ranged from 15.9 to 22, with an average of 18.2. During the last three interviews, no new themes or subthemes were identified, suggesting answer saturation.

3.2. Overview of Themes and Subthemes

The coding process identified four major themes: selective content, biased interpretation, behavioural adaptation, and recovery process. These themes were further divided into specific subthemes (see Figure 1).

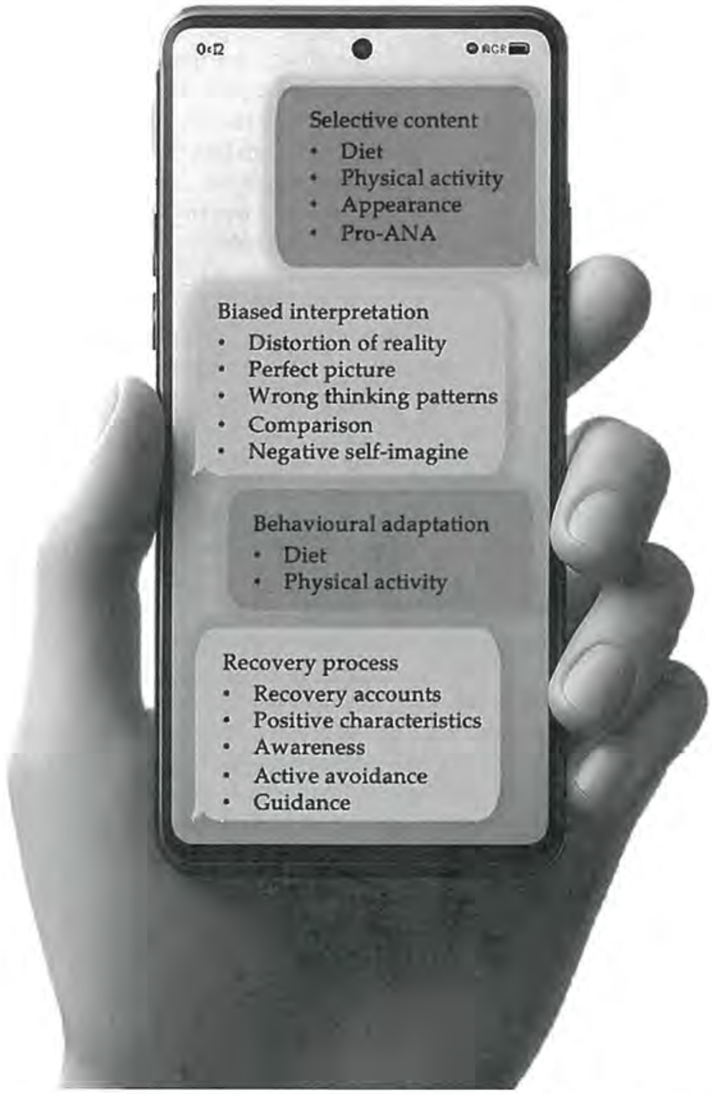

Figure 1. Overview of the main themes and subthemes influenced by social media.

3.3. *Selective Content*

Adolescents with eating disorders reported exposure to triggering content on social media. Some participants noted that they encountered such content even before their diagnosis, believing it may have contributed to the disorder's development. Pro-ANA materials were described as addictive, making active avoidance challenging. Eventually, they actively sought this content due to an intrinsic urge, leading to increased exposure as algorithms aligned with their interests.

> *Participant 3: "I think it is a kind of addiction after all, because I keep looking for the positive but then the negative always comes back."*

> *Participant 1: "Back then the content was all about eating, eating, eating and how meals were made, and how many calories it contained. If I didn't know the caloric content, I also pretended not to be interested in the hope that I would get other content including the calories."*

Participants encountered three types of eating disorder-related content: food, physical activity, and physical appearance. First, they were exposed to online content related to

diet and food intake. These online materials promoted a restrictive and selective diet. A substantial portion of the content to which they were exposed pertained to caloric content of various food items, and they received guidance to abstain from food with high caloric values. Consequently, exposure to "What I Eat in A Day" content engendered an excessive preoccupation with their food intake quantities. In addition to the avoidance of specific food items, recommendations for healthier food alternatives were provided.

> *Participant 3: "Very often counting calories was encouraged and suggestions were made like: 'these are healthier snacks, or these foods are not okay to consume.' Also, 'What I Eat in A Day'-videos but it was very little and hyper healthy."*

> *Participant 6: "I primarily monitored caloric intake myself, so I would search for this kind of information on the internet and occasionally encounter it on social media, such as individuals substituting bread with bell peppers, for example."*

The second type of content the participants preferred was related to physical activity, which provided tips for rapid weight loss. The combination of content related to maximal caloric expenditure during exercise and daily life, along with content related to reduced caloric intake, resulted in a negative energy balance.

> *Participant 7: "Sports that burn the most in a shorter time and so on. Climbing stairs and jumping rope and so on. And never sitting still with my legs, that I always have to move them when I sit."*

The final category of preferred content pertains to physical appearance. Participants exhibited a marked preference for content that idolized the slender physiques of models and influencers. This content contributed to the formation of an 'ideal body image' to which the participants aspired.

> *Participant 3: "Very often images of someone who is underweight or who is more like the ideal image and if you have an eating disorder you would look like that."*

3.4. Biased Interpretation

Participants showed a biased interpretation of online content, focusing on diet, physical activity, and appearance, even when this content was unrelated to eating disorders. This led to a distorted reality, often overlooking digital image manipulation. During recovery, their perception of reality shifted, as will be discussed later.

> *Participant 7 on selective focus: "Yes, I do look more at people's appearance and body and also, yes, still nutrition and so on and in terms of exercise. What people do. Before my eating disorder, I used to look mainly at creative things and cheerful things."*

> *Participant 1 on reflection of reality: "I see someone thin, and I want to be like that, or I want to be thinner. Social media was just the perfect image for me, and I had to meet those standards, and I saw the reality in that photo, and you don't immediately think: 'that could also be photoshopped'".*

The distorted reflection led to an incorrect thought pattern throughout the course of the eating disorder, resulting in a mindset that was equally fixated on the eating disorder and social approval. As previously indicated in the earlier quotations, one of the key factors is the comparison that the participants drew between the continuous triggering content on social media and themselves. The comparison applied to all previously mentioned content (food, physical activity and physical appearance), which resulted in negative emotional states and sometimes a preoccupation with certain body parts. This, in turn, gave rise to a negative spiral, resulting in self-disappointment, feelings of loneliness due to the emergence of a sense 'not to be good enough', and the development of shame and jealousy.

> *Participant 1: "Advertisements from people who would lose weight and say: 'now I'm much happier', then you want to be like that too, so you want to comply, and you want to lose weight to be happier too".*

> *Participant 3: "Yes, feeling sad, becoming very insecure about yourself. I also think that there is a certain fear of not fitting in or not being like the people on social media, so will I be accepted by society?"*

3.5. Behavioural Adaptation

Negative self-image and false thinking patterns are suggested to be the basis for behavioural changes, including adopting low-calorie recipes, avoiding specific foods or restricting food intake to certain times of the day. Additionally, engaging in extreme exercise and/or physical activity was observed, accompanied by a shift in actively seeking certain content, as stated above.

> *Participant 1: "For example, articles that advise you to eat more slowly and chew well. So yeah, it can apply to a lot of things: what you eat, how you eat, how much you eat, it can apply to everything."*

> *Participant 2: "Oh, look at them, they eat at that time, and they have their last meal at that time, and then I start thinking: 'I shouldn't eat before that hour, and I definitely shouldn't eat after that hour. I can only drink this and I definitely can't drink that and can only eat this'."*

> *Participant 4: "When I was in the midst of my eating disorder, it was mainly about things related to food, you know. A lot of 'What I Eat in A Day' stuff. And then, I was sort of comparing myself, and I was constantly looking at it to make sure I ate less."*

3.6. Recovery Process

Throughout the recovery process, a notable shift was observed in how participants interpreted online content, resulting in a different understanding and impact of digital materials. Initially, identifying triggering content was essential, and recognizing the impact of these comparisons on their emotional state was crucial. By altering their interpretation, participants gained insight into the distorted portrayals on social media and their adverse effects on recovery. This shift often led to actively avoiding specific social media content. Unlike the early stages of the illness, where there was a selective focus on eating disorder-related content, adopting an avoidant approach proved vital during recovery.

> *Participant 2 about awareness: "A lot of my friends use Facebook and so on, but I've already said, for example, that I'd rather not because I'm afraid of social media, because I know it can have an impact anyway".*

> *Participant 5 about active avoidance: "Yeah, as I mentioned earlier, those negative accounts, I just block them or something."*

Guidance from parents and caregivers was also essential in transforming the interpretation of online content and reducing negative comparisons. Counselling and supervision of social media use by parents and caregivers could assist adolescents in developing awareness and actively avoiding negative aspects of their social media use. Several participants emphasised that the role of this guidance should not be underestimated, as it expedites the transformation of the interpretation of online content and triggers, ultimately leading to an end of the continuous negative comparisons that were being made.

> *Participant 1: "You can't yet be aware that something is triggering, and if you're already aware of that and then dare to indicate that I don't really like this kind of content, I want to have something else on my social media, then I think you have to find your way in that, but that will come when you have guidance. I think it's hard to beat an eating disorder alone, the path that must be walked together."*

In addition to the potential for positive evolution through social media use, various types of content on these platforms were observed to contribute to this transformation. This includes content related to eating disorders, such as recovery testimonials, as well as other content categories. Recovery accounts facilitated positive evolution in participants

by presenting content that highlighted achievable outcomes if they overcame their eating disorder. This content helped in breaking stereotypes or taboos, alleviated feelings of loneliness by demonstrating shared experiences, promoted body positivity and self-love, and provided challenges related to eating. These elements seemed to trigger positive emotions in participants, such as recognition and motivation, and provided tools to challenge distorted thinking patterns, fostering a hopeful future perspective. However, it is important to note that these accounts could also serve as triggers when participants were in a negative emotional state, potentially leading them to perceive recovery as unattainable and inducing a sense of despair.

Participant 2: "That you are not allowed to feel bad, and that food is actually something that you need to live and to do things that you like to do. Trying to promote that kind of stuff, think about it carefully and not see it too negatively and that you are also allowed to enjoy something lesser, that it may not always be very healthy."

Participant 5: "These are mostly people who have experienced an eating disorder themselves. They share their experiences, detailing their journey in recovery and how it has positively influenced their choice to pursue and continue the path of healing."

Contact with peers, distraction, and inspiration from social media also contributed positively, helping to limit feelings of isolation and providing them with a degree of connection. Furthermore, social media could serve as a source of diversion, with it being perceived as a form of relaxation and creative inspiration for specific projects, fashion, or personal interests.

Participant 4: "I think that at times, I have certainly derived positive things from social media, such as friends who were there for me and sent me uplifting messages."

Participant 5: "Personally, I also draw a lot of inspiration, yeah, for creative pursuits. Or from fashion, outfit inspiration, and such."

4. Discussion

This study explored how adolescents with anorexia nervosa perceive social media content. Previous research indicates that social media influences disordered eating patterns, with exposure to "ideal beauty standards" leading to body dissatisfaction and unhealthy eating behaviours [20,21]. Once confined to magazines [22–24], this exposure has now increased with social media, worsening body dissatisfaction and problematic eating [3,25,26]. Recent studies suggest a causal link between social media and disordered eating. Participants who abstained from social media for a week showed fewer eating disorder symptoms compared to a control group [27].

Despite the growing evidence linking social media with eating disorders, research on its impact on adolescents already diagnosed with an eating disorder is limited. Our qualitative study identified four main themes regarding the influence of social media on the course of eating disorders: selective content (diet, physical activity, appearance, and pro-ANA), biased interpretation (distortion of reality, perfect picture, wrong thinking patterns, comparison, negative self-image), behavioural adaptation (diet and physical activity), and the recovery process (awareness, active avoidance, guidance, positive characteristics, and recovery accounts).

The first main theme concerns the content of social media and its link to eating disorders. Our data indicate that social media content related to physical appearance significantly influences both the initiation and perpetuation of eating disorders. This is consistent with other studies showing that adolescents compare themselves to unrealistic portrayals of bodies, leading to body dissatisfaction and unhealthy eating behaviours [28,29]. This trend, often termed "thinspiration" or "fitspiration", was frequently encountered by our study participants [30–32].

Our data revealed that adolescents in the early stages of eating disorders actively seek content related to food intake and fitspiration. Videos like "What I Eat in A Day" serve as consumption benchmarks [33], potentially distorting thought patterns regarding daily food

intake even among healthy adolescents [34]. Moreover, pro-ANA (pro-anorexia) content was identified as triggering by our participants. Previous studies already documented its adverse impact on the quality of life and its potential to prolong eating disorders [35]. Participants noted that seeking food and pro-ANA content led to more exposure due to algorithmic recommendations [36].

The second major theme involved the distorted interpretation of social media content. Previous studies have shown higher rates of eating disorder-related behaviours and self-comparison in individuals who spend more time on social media [37,38]. This comparative behaviour is influenced by peers [39] and influencers who promote an idealized body image, negatively impacting mood and body dissatisfaction [40]. Our data highlight the central role of comparison in perpetuating negative emotions, with photo manipulation tools like Photoshop exacerbating body dissatisfaction [41,42].

The third theme, behavioural adaptation, specifically concerns changes in food intake and physical activity. Prior studies have identified both direct and indirect links between social media exposure and eating behaviours among healthy adolescents and young adults [43]. Exposure to fitspiration and thinspiration was associated with disordered eating behaviours, such as purging and restrictive dieting, in female university students [27]. Our findings align with these observations, with participants describing shifts towards more selective and restrictive diets influenced by online examples. A recent review article corroborated this relationship, noting the association between exposure to food-related content on social media, body image problems and disturbed eating behaviour [44]. A randomized controlled trial of adolescent girls found that more social media use led to greater influence on distorted food intake thoughts and behaviours in adolescent girls [3].

Participants reported that social media examples of physical activity encouraged extreme and unhealthy habits. This aligns with research showing postpartum women exposed to appearance-focused social media exhibited more distorted eating and unhealthy physical activity desires [45]. Conversely, social media can also promote healthy habits as demonstrated by a cross-sectional analysis where one-third of adolescents with obesity increased their physical activity through social media [40]. Given social media's dual impact on adolescents' physical activity behaviours, it seems to be crucial to provide guidance and education on appropriate social media use.

The final theme concerns social media's role in the recovery process. When used appropriately, social media can support recovery by facilitating interaction with online recovery communities. An online qualitative survey of adults engaged with recovery accounts on Instagram highlighted both positive and negative aspects of social media during recovery, similar to our findings [46]. Contact with peers on recovery accounts fosters a sense of community and understanding, with recovery journeys serving as motivation and inspiration.

We identified three primary factors influencing recovery: awareness, active avoidance, and guidance. Participants' growing awareness of social media's impact led to more mindful use, often resulting in the active avoidance of certain media. This selective use, documented in other studies, correlates with decreased eating disorder-related cognition and behaviours [3,44]. Furthermore, educational interventions on social media literacy have been shown to reduce risk factors for developing eating disorders, highlighting the potential of guidance in facilitating awareness and active avoidance [46]. However, social media can also expose users to certain triggers during recovery. One study highlighted various negative consequences of using recovery accounts, such as the underrepresentation of different body types, content focused on appearance, and misinformation [47], aspects not observed in our study.

Our study has several limitations. During the recruitment process, it became evident that many adolescents diagnosed with an eating disorder were reluctant to participate due to the difficulty of discussing the subject. However, after five interviews, no new themes emerged, suggesting answer saturation. Therefore, we consider the number of

participants to be sufficient. Given that this study employs a qualitative approach with in-depth interviews in a homogenous group, the primary focus is on understanding the "how" and exploring the "various relationships between the investigated categories" rather than proving a specific hypothesis [48,49]. Malterud et al. (2016) introduced the concept of information power to assess sample size. Given our narrow study aim, highly specific participant selection and the desire for in-depth analysis, a smaller sample size is sufficient [50].

The qualitative nature of our study makes it susceptible to various biases that could influence our findings and interpretations. To address selection bias, we carefully defined inclusion and exclusion criteria and specified the study population beforehand. Notably, the average duration of the eating disorder among participants was 18 months, indicating they were in a more advanced stage of recovery with significant experience of social media's influence.

During interviews, the primary researchers used a guiding rather than a directive approach to prevent interviewer bias. The interview guide started with broad, general questions before moving to more detailed and specific topics, minimizing the influence of question sequencing. Additionally, the interviews were conducted by the primary researchers rather than the treating physicians, allowing participants to speak freely and thus minimizing response bias. The use of semi-structured interviews with specific main questions may have led to the exclusion of certain topics, potentially missing essential triggers. Our focus was on the eating disorder process itself, rather than solely on the recovery process, which may explain the fewer themes identified compared to other studies. Additionally, the interview structure allowed for sub-questions based on respondents' answers, leading to a more extensive exploration of some topics. This may have created the impression that these topics played a more significant role in maintaining the eating disorder or influencing the recovery process.

5. Conclusions

In conclusion, this study examined the impact of social media on adolescents with anorexia nervosa through semi-structured interviews. Four key themes emerged, illustrating the complex relationship between social media and eating disorders:

- Content focused on eating disorders: Social media content related to physical appearance promotes unrealistic body ideals, leading to body dissatisfaction and unhealthy eating behaviours.
- Biased interpretation: Comparison and distorted perceptions, often influenced by social media influencers and photo manipulation, contribute to negative emotions and persistent body dissatisfaction.
- Behavioural adaptation: Exposure to social media content alters food intake and physical activity patterns.
- Recovery process: Awareness and active avoidance of social media can aid recovery, though guidance is necessary to harness social media's positive aspects.

The study underscores the importance of continued research to validate and understand the diverse impacts of social media on eating disorders, highlighting both potential triggers and beneficial aspects.

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6

JAMA | Original Investigation

Addictive Screen Use Trajectories and Suicidal Behaviors, Suicidal Ideation, and Mental Health in US Youths

Yunyu Xiao, PhD; Yuan Meng, PhD; Timothy T. Brown, PhD; Katherine M. Keyes, PhD; J. John Mann, MD

Editorial

Supplemental content

IMPORTANCE Increasing child and adolescent use of social media, video games, and mobile phones has raised concerns about potential links to youth m
research has largely focused on total screen time rather than
trajectories.

OBJECTIVES To identify trajectories of addictive use of social
games and to examine their associations with suicidal behav
health outcomes among youths.

DESIGN, SETTING, AND PARTICIPANTS Cohort study analyzing
year 4 follow-up in the Adolescent Brain Cognitive Developr
population-based samples from 21 US sites.

EXPOSURES Addictive use of social media, mobile phones, a
child-reported measures from year 2, year 3, and year 4 follo

MAIN OUTCOMES AND MEASURES Suicidal behaviors and ide
and parent-reported information via the Kiddie Schedule fo
Schizophrenia. Internalizing and externalizing symptoms we
parent-reported Child Behavior Checklist.

RESULTS The analytic sample (n = 4285) had a mean age of
female; and 9.9% were Black, 19.4% Hispanic, and 58.7% W
models identified 3 addictive use trajectories for social media and mobile phones and 2 for video games. Nearly one-third of participants had an increasing addictive use trajectory for social media or mobile phones beginning at age 11 years. In adjusted models, increasing addictive use trajectories were associated with higher risks of suicide-related outcomes than low addictive use trajectories (eg, increasing addictive use of social media had a risk ratio of 2.14 [95% CI, 1.61-2.85] for suicidal behaviors). High addictive use trajectories for all screen types were associated with suicide-related outcomes (eg, high-peaking addictive use of social media had a risk ratio of 2.39 [95% CI, 1.66-3.43] for suicidal behaviors). The high video game addictive use trajectory showed the largest relative difference in internalizing symptoms (T score difference, 2.03 [95% CI, 1.45-2.61]), and the increasing social media addictive use trajectory for externalizing symptoms (T score difference, 1.05 [95% CI, 0.54-1.56]), compared with low addictive use trajectories. Total screen time at baseline was not associated with outcomes.

CONCLUSIONS AND RELEVANCE High or increasing trajectories of addictive use of social media, mobile phones, or video games were common in early adolescents. Both high and increasing addictive screen use trajectories were associated with suicidal behaviors and ideation and worse mental health.

DEPRESSION

&

SUICIDALITY

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Yunyu Xiao, PhD; Yuan Meng, PhD; Timothy T. Brown, PhD; Katherine M. Keyes, PhD; J. John Mann, MD

Editorial

Supplemental content

IMPORTANCE Increasing child and adolescent use of social media, video games, and mobile phones has raised concerns about potential links to youth mental health problems. Prior research has largely focused on total screen time rather than longitudinal addictive use trajectories.

OBJECTIVES To identify trajectories of addictive use of social media, mobile phones, and video games and to examine their associations with suicidal behaviors and ideation and mental health outcomes among youths.

DESIGN, SETTING, AND PARTICIPANTS Cohort study analyzing data from baseline through year 4 follow-up in the Adolescent Brain Cognitive Development Study (2016-2022), with population-based samples from 21 US sites.

EXPOSURES Addictive use of social media, mobile phones, and video games using validated child-reported measures from year 2, year 3, and year 4 follow-up surveys.

MAIN OUTCOMES AND MEASURES Suicidal behaviors and ideation assessed using child- and parent-reported information via the Kiddie Schedule for Affective Disorders and Schizophrenia. Internalizing and externalizing symptoms were assessed using the parent-reported Child Behavior Checklist.

RESULTS The analytic sample (n = 4285) had a mean age of 10.0 (SD, 0.6) years; 47.9% were female; and 9.9% were Black, 19.4% Hispanic, and 58.7% White. Latent class linear mixed models identified 3 addictive use trajectories for social media and mobile phones and 2 for video games. Nearly one-third of participants had an increasing addictive use trajectory for social media or mobile phones beginning at age 11 years. In adjusted models, increasing addictive use trajectories were associated with higher risks of suicide-related outcomes than low addictive use trajectories (eg, increasing addictive use of social media had a risk ratio of 2.14 [95% CI, 1.61-2.85] for suicidal behaviors). High addictive use trajectories for all screen types were associated with suicide-related outcomes (eg, high-peaking addictive use of social media had a risk ratio of 2.39 [95% CI, 1.66-3.43] for suicidal behaviors). The high video game addictive use trajectory showed the largest relative difference in internalizing symptoms (T score difference, 2.03 [95% CI, 1.45-2.61]), and the increasing social media addictive use trajectory for externalizing symptoms (T score difference, 1.05 [95% CI, 0.54-1.56]), compared with low addictive use trajectories. Total screen time at baseline was not associated with outcomes.

CONCLUSIONS AND RELEVANCE High or increasing trajectories of addictive use of social media, mobile phones, or video games were common in early adolescents. Both high and increasing addictive screen use trajectories were associated with suicidal behaviors and ideation and worse mental health.

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The increasing use of social media, video games, mobile phones, and other screen-based activities among adolescents, combined with rising rates of suicidal behaviors and mental health problems in children and younger adolescents, has raised concerns,[1-4] including a US surgeon general warning label.[5] While most existing research has focused on total screen time,[6-11] emerging evidence suggests that addictive screen use may be a more salient risk factor for suicidality and mental health in youths.[12-15] Addictive use may vary by platform[16,17] and follow distinct developmental trajectories. However, addictive use trajectories among youths have not been well characterized, and how they may relate to suicide-related and mental health outcomes remains largely unknown.[18,19]

To address these gaps, this study used nationwide data from the Adolescent Brain Cognitive Development (ABCD) Study, a population-based, longitudinal cohort of children and adolescents, to (1) characterize longitudinal trajectories of addictive use of social media, mobile phones, and video games; (2) assess whether addictive use trajectories were associated with suicidal behaviors, suicidal ideation, and internalizing and externalizing symptoms over 4 years, controlling for baseline demographics and clinical characteristics; and (3) examine whether addictive use trajectories were associated with outcomes after adjusting for total screen time.

Key Points

Question Are addictive screen use trajectories associated with suicidal behaviors, suicidal ideation, and mental health outcomes in US youth?

Findings In this cohort study of 4285 US adolescents, 31.3% had increasing addictive use trajectories for social media and 24.6% for mobile phones over 4 years. High or increasing addictive use trajectories were associated with elevated risks of suicidal behaviors or ideation compared with low addictive use. Youths with high-peaking or increasing social media use or high video game use had more internalizing or externalizing symptoms.

Meaning Both high and increasing addictive screen use trajectories were associated with suicidal behaviors, suicidal ideation, and worse mental health in youths.

Methods

This study used the most recent available data from the ABCD Study (release 5.1),[20] a longitudinal cohort study of participants aged 9 to 10 years recruited from 21 US sites at baseline (n = 11 868) and followed up annually. Data collection spanned 2016 through January 2022, covering both the COVID-19 prepandemic and postpandemic years. Because the 4-year follow-up data release is ongoing, we used the available random subset (n = 4754). χ^2 Automatic interaction detection (CHAID) analysis comparing baseline characteristics of participants with and without year 4 follow-up data showed no selection bias (eAppendix 1 in Supplement 1).[21]

Our analytic sample included 4285 participants with complete data on addictive screen use from the year 2 to year 4 follow-up surveys and baseline demographics (**Figure 1**).[22-24] This study was approved by institutional review boards at each site, with central institutional review board approval from the University of California, San Diego. Parents or guardians provided written informed consent. This study follows the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) reporting guideline.

Addictive Screen Use (Years 2-4 Follow-Up)

Validated self-report questionnaires[25,26] were used to assess addictive uses for 3 platforms—social media, mobile phones, and video games—including a 6-item Social Media Addiction Questionnaire (SMAQ), 8-item Mobile Phone Involvement Questionnaire (MPIQ), and 6-item Video Game Addiction Questionnaire (VGAQ),[27,28] measuring compulsive use, difficulty disengaging, and distress when not using (see details in the Box and in eTable 1 in Supplement 1). Responses used Likert-type scales (1 ["never"] to 6 ["very often"] for SMAQ and VGAQ; 1 ["strongly disagree"] to 7 ["strongly agree"] for MPIQ). We calculated weighted addictive use scores using confirmatory factor analysis,[22] which were appropriate for this study because of their greater measurement precision and construct validity than mean scores (eTable 1 and eAppendix 2 in Supplement 1).[29] Higher scores indicate greater addictive use. All scales have high reliability (Cronbach $\alpha = 0.88$ for each scale) (eTable 2 in Supplement 1).

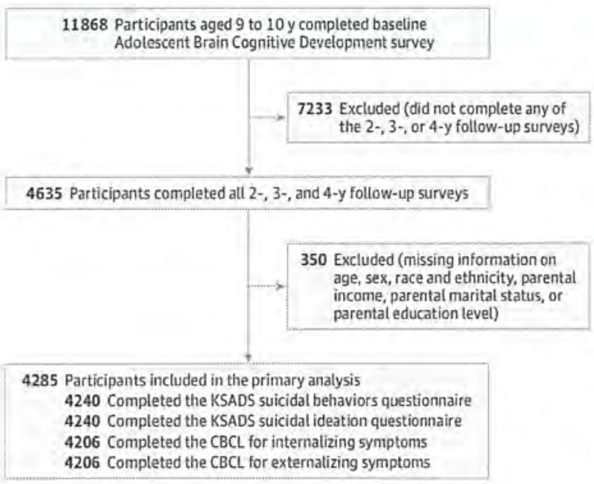
Total Screen Time (Baseline)

Because different screen activities can overlap, this analysis used self-reported questions assessing the average daily non-schoolwork-related screen time (separately for weekdays and weekends) (eTable 1 in Supplement 1). Prior ABCD studies showed positive correlations between self-reported and objectively measured screen use ($r = 0.49$; $P < .001$).[6]

Suicidal Behaviors and Suicidal Ideation (Year 4 Follow-Up)

Child and parent reports of suicidal behaviors and suicidal ideation over the prior year were assessed at year 4 follow-up using the Kiddie Schedule for Affective Disorders and Schizophrenia (KSADS),[30,31] covering a spectrum of suicide-related outcomes: (1) passive ideation; (2) nonspecific active suicidal ideation; (3) specific active suicidal ideation; (4) active ideation with intent; (5) active ideation with plan and intent; (6) preparatory actions for imminent suicidal behavior; (7) interrupted suicidal attempt; (8) aborted suicidal attempt; and (9) suicide attempt (eTable 3 in Supplement 1). Consistent with prior literature,[32,33] suicidal ideation was classified as present if any of items 1 to 5 were endorsed, and suicidal behaviors were classified as present if any of items 6 to 9 were endorsed, by either the youth or caregiver. The KSADS exhibits strong validity and reliability for this population.[30]

Figure 1. Participant Flow in a Study of Addictive Screen Use Trajectories and Suicidal Behaviors and Ideation and Mental Health in Youths



CBCL indicates Child Behavior Checklist; KSADS, Kiddie Schedule for Affective Disorders and Schizophrenia.

Mental Health Outcomes (Year 4 Follow-Up)

Analyses included current parent-reported internalizing (eg, anxiety, depression) and externalizing (eg, aggression, rule-breaking) symptoms using T scores derived from the Child Behavior Checklist (CBCL).[29] T scores of 65 or greater are considered to indicate clinically elevated symptoms.[34]

Covariates (Baseline)

Models were adjusted for child age, sex, race and ethnicity, parental income, education, and marital status as reported in the baseline ABCD parent demographics survey. Race and ethnicity were based on caregiver-reported predefined categories, including non-Hispanic Asian, non-Hispanic Black, Hispanic (any race), non-Hispanic White, and multiracial and/or other racial and ethnic groups, collected as social constructs to investigate the differential impact of structural disadvantages (eTable 3 in Supplement 1).[35,36] Models were also adjusted for baseline clinical characteristics (ie, suicidal behaviors, suicidal ideation, and internalizing and externalizing symptoms).

Statistical Analysis

Latent class linear mixed models[37] were used to identify addictive use trajectories based on age and quadratic age terms (eAppendix 3 in Supplement 1). In the addictive use questionnaires, missing data resulting from skip patterns based on previous use or nonuse questions were replaced with "1 = never/strongly disagree" for participants who reported having no social media accounts or mobile phones or who did not play video games. The optimal group-based trajectory model was selected based on (1) the lowest bayesian information criterion; (2) greater than 70% average probability of participants being correctly classified into their respective trajectories; (3) greater than 5.0 odds of correct classification; and (4) greater than 5% minimum trajectory sample sizes out of the total sample. Each addictive use trajectory represents children who shared similar addictive use levels over time.

Box. Sample Items From Addictive Use Scales and Baseline Screen Time Measures[a]

Addictive Use (Social Media/Mobile Phone/Video Games)

- I feel the need to use social media apps more and more (1 [never] to 6 [very often]).
- The thought of being without my phone makes me feel distressed (1 [strongly disagree] to 7 [strongly agree]).
- I play video games so I can forget about my problems (1 [never] to 6 [very often]).

Total Screen Time (Weekday/Weekend)

Total typical weekend and weekday screen times on streaming movies or television shows, single-player games, multiplayer games, texting, social media, and video chatting (0-24 hours).

[a] eTable 1 in Supplement 1 is a full table of addictive use and screen time measures.

Subsequently, these addictive use trajectories were treated as categorical variables in outcome models. For categorical outcomes (suicidal behaviors and suicidal ideation), Poisson regression models were used to estimate risk ratios (RRs), with 95% CIs calculated using robust standard errors. Poisson models are appropriate in this context.[38-40] For continuous outcomes (internalizing and externalizing symptoms), generalized linear models were used to estimate mean differences, with 95% CIs calculated using ordinary standard errors. E-values were computed to evaluate sensitivity to unmeasured confounding.[41] Total screen time was added as a covariate to examine whether it explained the magnitude or direction of the associations between addictive use trajectories and outcomes. In the sensitivity analysis, total screen time was also tested for independent associations with the outcomes.

Significance was set at a 2-sided $P < .05$, corrected for false discovery rate (FDR) using the Benjamini-Hochberg method to adjust for multiple testing within each group.[42] All analyses were conducted in R version 4.3.1 (R Foundation).

Results

Among 4285 participants (baseline mean age, 10.0 [SD, 0.6] years; 47.9% female), the sample included 96 (2.2%) Asian, 426 (9.9%) Black, 830 (19.4%) Hispanic, and 2515 (58.7%) White individuals, as well as 418 (9.8%) individuals identifying as multiracial and/or other races (**Table**).

Addictive Use Trajectories

The optimal trajectory models were selected based on multiple fit criteria (eTable 4 and eAppendix 4 in Supplement 1).

For social media, 3 addictive use trajectories emerged (**Figure 2**): high-peaking (n = 410 [9.6%]), increasing (n = 1342 [31.3%]), and low (n = 2533 [59.1%]). At baseline, high-peaking and increasing trajectories had similar levels of

Table. Baseline Characteristics and Year 4 Follow-Up Suicidal Behaviors, Suicidal Ideation, and Mental Health Outcomes

Characteristics	No. (%) [n = 4285]
Age, mean (SD), y	10.0 (0.6)
Sex	
Female	2051 (47.9)
Male	2234 (52.1)
Race and ethnicity	
Asian	96 (2.2)
Black	426 (9.9)
Hispanic	830 (19.4)
White	2515 (58.7)
Multiracial and/or other[a]	418 (9.8)
Annual household income, $	
<75 000	1722 (40.2)
≥75 000	2563 (59.8)
Parental marital status	
Married	3138 (73.2)
Living with partner	197 (4.6)
Single	950 (22.2)
Parental education	
Less than bachelor's degree	1474 (34.4)
Bachelor's or higher	2811 (65.6)
Suicidal behaviors (year 4 follow-up)[b]	
No	4036 (94.9)
Yes	218 (5.1)
Suicidal ideation (year 4 follow-up)[c]	
No	3494 (82.1)
Yes	760 (17.9)
Child Behavior Checklist T score, mean (SD)[d]	
Internalizing symptoms	47.5 (10.8)
Externalizing symptoms	43.4 (9.3)

[a] Primary caregivers were allowed to choose multiple race subgroups for children; the "other" category indicates that no specific race or ethnicity group was identified.

[b] Suicidal behaviors were determined if any of the questions for the following Kiddie Schedule for Affective Disorders and Schizophrenia (KSADS) items had a "yes" response by the child or the caregiver: (1) preparatory actions for imminent suicidal behavior; (2) interrupted suicidal attempt; (3) aborted suicidal attempt; and (4) suicide attempt.

[c] Suicidal ideation was determined if any of the questions for the following KSADS items had a "yes" response by the child or the caregiver: (1) passive ideation; (2) nonspecific active suicidal ideation; (3) specific active suicidal ideation; (4) active ideation with intent; and (5) active ideation with plan and intent.

[d] Child Behavior Checklist T scores for internalizing range from 33 to 87 and for externalizing range from 33 to 82. T scores are standard scores derived from raw scores. Higher T scores reflect more severe internalizing and externalizing symptoms; T scores of 65 or greater indicate clinically meaningful internalizing and externalizing concerns.

social media addictive use, providing no clear indication of their subsequent divergence. By age 14 years, the increasing social media addictive use trajectory reached levels comparable with the high-peaking addictive use trajectory and continued to rise further.

Mobile phone addictive use also followed 3 trajectories: high (n = 2109 [49.2%]), increasing (n = 1052 [24.6%]), and low (n = 1124 [26.2%]). The low and increasing addictive use trajectories began with almost the same baseline levels but diverged in their subsequent trajectories. The increasing mobile phone addictive use trajectory showed a steady increase in its addictive use level in the following 4 years, reaching levels comparable with the high addictive use trajectory by age 15 years.

For video games, 2 trajectories were identified: high addictive use (n = 1761 [41.1%]) and low addictive use (n = 2524 [58.9%]).

Trajectory Differences in Baseline Demographics and Clinical Characteristics

The high addictive social media use trajectory included a higher proportion of females than the low addictive use trajectory (51.0% vs 42.8%; absolute difference, 8.18%; 95% CI, 3.07%-13.36%) (eTable 5 in Supplement 1). In contrast, youths in high addictive video game use trajectories were more likely to be male than those in low addictive use trajectories (70.1% vs 39.6%; absolute difference, 30.55%; 95% CI, 27.64%-33.40%).

Youths in high addictive use trajectories were more likely to be Black (absolute differences, 3.08%-7.91%) or Hispanic (absolute differences, 7.12%-10.03%) compared with those in low addictive use trajectories.

High addictive use trajectories also had higher proportions of youths from households with annual incomes below $75 000, unmarried parents, and parents with less than a bachelor's degree education (absolute differences across these indicators ranged from 1.55% to 18.95%) compared with low addictive use trajectories.

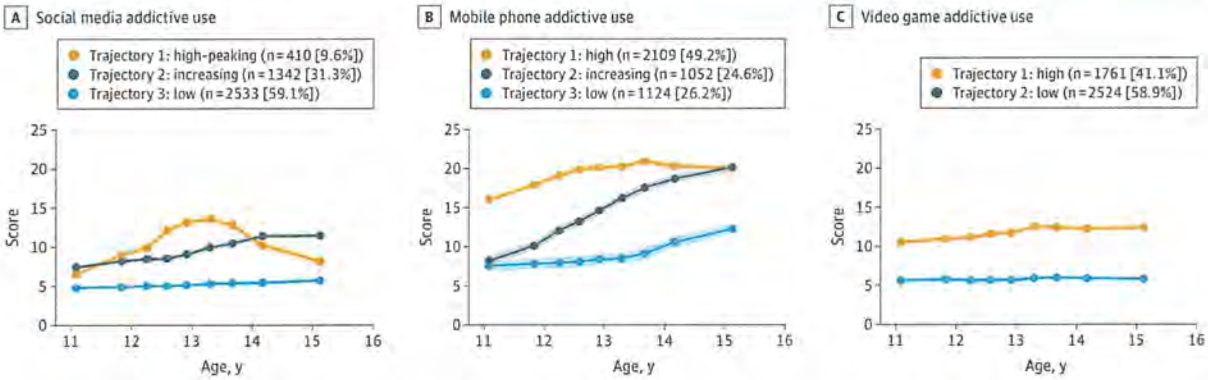
Youths in high addictive social media use trajectories had the largest differences in baseline suicidal behaviors (absolute difference, 1.67%; 95% CI, 0.06%-3.50%) and baseline externalizing symptom scores (absolute T score mean difference, 1.79; 95% CI, 0.75-2.82) compared with those in low addictive use trajectories. The largest differences in baseline suicidal ideation (absolute difference, 6.79%; 95% CI, 4.58%-8.91%) and baseline internalizing symptom scores (absolute T score mean difference, 1.80; 95% CI, 1.19-2.44) were observed between the groups in high and low addictive use trajectories for video games.

Associations of Trajectories of Addiction Severity With Suicidal Behaviors, Suicidal Ideation, and Mental Health

Among 4285 participants, 218 (5.1%) reported suicidal behaviors and 760 (17.9%) reported suicidal ideation at year 4 follow-up. Mean year 4 CBCL internalizing and externalizing T scores were 47.5 (SD, 10.8) and 43.4 (SD, 9.3), respectively (Table).

For social media addictive use, adjusted models (**Figure 3**) showed that both high-peaking and increasing addictive use trajectories were associated with higher risk of suicidal behaviors (high-peaking: RR, 2.39; 95% CI, 1.66-3.43; FDR-adjusted $P < .001$; increasing: RR, 2.14; 95% CI, 1.61-2.85; FDR-adjusted $P < .001$) and elevated risk of suicidal ideation (high-peaking: RR, 1.51; 95% CI, 1.25-1.83; FDR-adjusted $P < .001$; increasing: RR, 1.46; 95% CI, 1.28-1.67;

Figure 2. Addictive Use Trajectories of Social Media, Mobile Phones, and Video Games



Latent class linear mixed models were used to identify distinct trajectories for each type of addictive use based on repeated measures of self-reported use of social media, mobile phones, and video games from ages 11 to 15 years. Each trajectory represents a group of children with similar temporal patterns of addictive use. Models were fit separately for each screen type and regressed on age and quadratic age terms. Model selection was based on the lowest bayesian information criterion, an average posterior probability of assignment greater than 70%, an odds of correct classification greater than 5.0, and a minimum group size of 5% (eTable 4 in Supplement 1). Addictive use scores were derived from confirmatory factor analysis (eTable 2 and eAppendix 2 in Supplement 1) and ranged as follows: social media, 4.5-26.8; mobile phone, 5.6-39.5; and video games, 4.5-26.9. Shaded areas represent 95% CIs. Data points along each trajectory line represent model-estimated mean scores at specific ages based on the latent class linear mixed models. Age values reflect quantiles of the observed age distribution.

FDR-adjusted $P < .001$) compared with the low addictive use trajectory. Internalizing symptom T scores were higher in the increasing addictive use trajectory (mean difference, 1.27; 95% CI, 0.66-1.88; FDR-adjusted $P < .001$), while externalizing symptom T scores were higher in both high-peaking (mean difference, 1.25; 95% CI, 0.45-2.04; FDR-adjusted $P = .004$) and increasing (mean difference, 1.05; 95% CI, 0.54-1.56; FDR-adjusted $P < .001$) addictive use trajectories compared with the low addictive use trajectory, all having small effect sizes (Cohen $d < 2$).

For mobile phone use, the high addictive use trajectory was associated with higher risks of suicidal behaviors (RR, 2.17; 95% CI, 1.48-3.19; FDR-adjusted $P < .001$) and suicidal ideation (RR, 1.50; 95% CI, 1.27-1.78; FDR-adjusted $P < .001$) compared with the low addictive use trajectory. The increasing addictive use trajectory was modestly associated with a greater relative risk of suicidal ideation (RR, 1.22; 95% CI, 1.01-1.48; FDR-adjusted $P < .001$) but not with other mental health outcomes.

For video game addictive use, the high addictive use trajectory was associated with higher risk of suicidal behaviors (RR, 1.54; 95% CI, 1.18-2.03; FDR-adjusted $P = .004$) and suicidal ideation (RR, 1.53; 95% CI, 1.35-1.75; FDR-adjusted $P < .001$), as well as higher internalizing symptom T scores (mean difference, 2.03; 95% CI, 1.45-2.61; FDR-adjusted $P < .001$) and externalizing symptom T scores (mean difference, 0.94; 95% CI, 0.45-1.43; FDR-adjusted $P < .001$) compared with the low addictive use trajectory.

Baseline total screen time alone was not associated with suicidal behaviors, suicidal ideation, or internalizing or externalizing symptom associations (**Figure 4**). Additionally, when models were adjusted for addictive use trajectories, baseline screen time remained not independently associated with these outcomes (eFigures 1-3 in Supplement 1). E-values indicated moderate to strong robustness to potential unmeasured confounding (range, 1.10-4.21).

Discussion

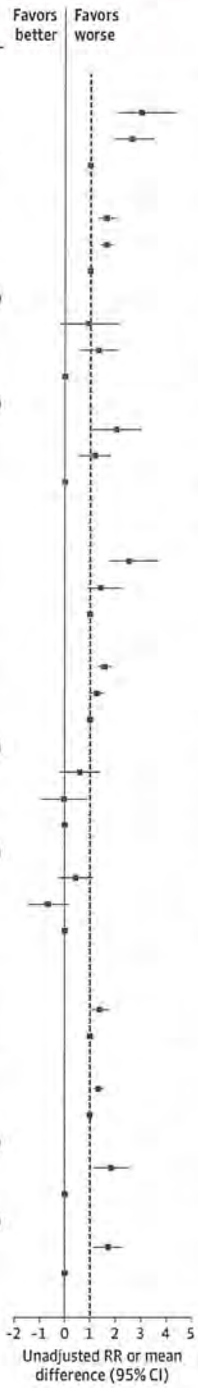
This study identified distinct trajectories of addictive use of social media, mobile phones, and video games from childhood to early adolescence and found links to suicidal behaviors, suicidal ideation, and worse mental health outcomes. High or increasing addictive use trajectories were common. Almost 1 in 2 youths had a high addictive use trajectory for mobile phones, and more than 40% had a high addictive use trajectory for video games. Many others had increasing addictive use over the 4-year observation period that ended with high addictive use; almost 1 in 3 had this trajectory for social media and 1 in 4 for mobile phones.

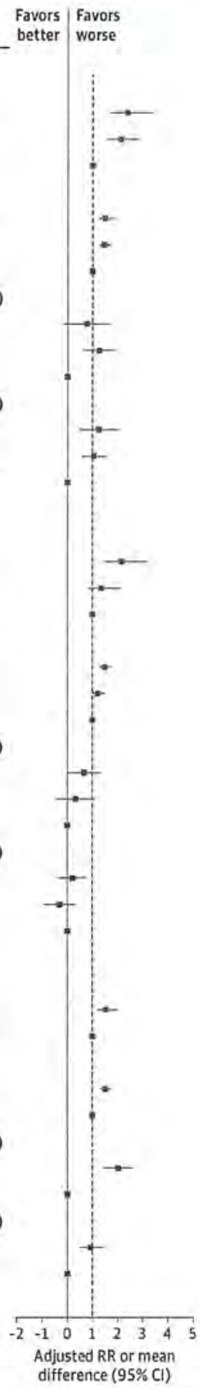
For social media and mobile phones, both the high and increasing addictive use trajectories were associated with 2 to 3 times greater risks of suicidal behaviors and suicidal ideation compared with the low addictive use trajectory. High-peaking and increasing addictive use trajectories of social media were also associated with higher internalizing and externalizing symptom scores compared with the low addictive use trajectory. For video games, the high addictive use trajectory was associated with greater risks of suicidal behaviors, suicidal ideation, and higher internalizing symptoms scores compared with the low addictive use trajectory.

To our knowledge, this is the first study to characterize longitudinal addictive use trajectories for social media, mobile phones, and video games among children and early adolescents and to assess their prospective associations with suicide-related and mental health outcomes. Specific strengths include

Figure 3. Associations of Addictive Use Trajectories With Year 4 Follow-Up Suicidal Behaviors, Suicidal Ideation, and Mental Health Outcomes

Outcomes, by trajectory[a]	No./total No. (%) With outcome	Without outcome	Unadjusted RR or mean difference (95% CI)[b]	Adjusted RR or mean difference (95% CI)[b]
Social media addictive use				
Suicidal behaviors			RR (95% CI)	RR (95% CI)
High-peaking	36/407 (8.8)	371/407 (91.2)	3.00 (2.05 to 4.38)	2.39 (1.66 to 3.43)
Increasing	105/1326 (7.9)	1221/1326 (92.1)	2.61 (1.96 to 3.48)	2.14 (1.61 to 2.85)
Low	76/2507 (3.0)	2431/2507 (97.0)	1 [Reference]	1 [Reference]
Suicidal ideation			RR (95% CI)	RR (95% CI)
High-peaking	94/407 (23.1)	313/407 (76.9)	1.64 (1.34 to 2.00)	1.51 (1.25 to 1.83)
Increasing	305/1326 (23.0)	1021/1326 (77.0)	1.62 (1.41 to 1.86)	1.46 (1.28 to 1.67)
Low	357/2507 (14.2)	2150/2507 (85.8)	1 [Reference]	1 [Reference]
CBCL internalizing			Mean difference (95% CI)	Mean difference (95% CI)
High-peaking	36/403 (8.9)	367/403 (91.1)	0.93 (-0.20 to 2.07)	0.78 (-0.17 to 1.73)
Increasing	138/1315 (10.5)	1177/1315 (89.5)	1.33 (0.61 to 2.05)	1.27 (0.66 to 1.88)
Low	165/2488 (6.6)	2323/2488 (93.4)	[Reference]	[Reference]
CBCL externalizing			Mean difference (95% CI)	Mean difference (95% CI)
High-peaking	25/403 (6.2)	378/403 (93.8)	2.03 (1.06 to 3.00)	1.25 (0.45 to 2.04)
Increasing	38/1315 (2.9)	1277/1315 (97.1)	1.18 (0.57 to 1.80)	1.05 (0.54 to 1.56)
Low	45/2488 (1.8)	2443/2488 (98.2)	[Reference]	[Reference]
Mobile phone addictive use				
Suicidal behaviors			RR (95% CI)	RR (95% CI)
High	146/2085 (7.0)	1939/2085 (93.0)	2.52 (1.72 to 3.69)	2.17 (1.48 to 3.19)
Increasing	41/1040 (3.9)	999/1040 (96.1)	1.41 (0.89 to 2.24)	1.35 (0.86 to 2.12)
Low	30/1115 (2.7)	1085/1115 (97.3)	1 [Reference]	1 [Reference]
Suicidal ideation			RR (95% CI)	RR (95% CI)
High	435/2085 (20.9)	1650/2085 (79.1)	1.57 (1.32 to 1.86)	1.50 (1.27 to 1.78)
Increasing	173/1040 (16.6)	867/1040 (83.4)	1.26 (1.03 to 1.54)	1.22 (1.01 to 1.48)
Low	148/1115 (13.3)	967/1115 (86.7)	1 [Reference]	1 [Reference]
CBCL internalizing			Mean difference (95% CI)	Mean difference (95% CI)
High	180/2067 (8.7)	1887/2067 (91.3)	0.58 (-0.20 to 1.37)	0.66 (0.00 to 1.33)
Increasing	79/1030 (7.7)	951/1030 (92.3)	-0.04 (-0.95 to 0.88)	0.32 (-0.44 to 1.08)
Low	80/1109 (7.2)	1029/1109 (92.8)	[Reference]	[Reference]
CBCL externalizing			Mean difference (95% CI)	Mean difference (95% CI)
High	57/2067 (2.8)	2010/2067 (97.2)	0.43 (-0.25 to 1.10)	0.20 (-0.36 to 0.76)
Increasing	20/1030 (1.9)	1010/1030 (98.1)	-0.66 (-1.44 to 0.13)	-0.30 (-0.94 to 0.33)
Low	31/1109 (2.8)	1078/1109 (97.2)	[Reference]	[Reference]
Video game addictive use				
Suicidal behaviors			RR (95% CI)	RR (95% CI)
High	106/1749 (6.1)	1643/1749 (93.9)	1.38 (1.06 to 1.78)	1.54 (1.18 to 2.03)
Low	111/2491 (4.5)	2380/2491 (95.5)	1 [Reference]	1 [Reference]
Suicidal ideation			RR (95% CI)	RR (95% CI)
High	366/1749 (20.9)	1383/1749 (79.1)	1.34 (1.18 to 1.52)	1.53 (1.35 to 1.75)
Low	390/2491 (15.7)	2101/2491 (84.3)	1 [Reference]	1 [Reference]
CBCL internalizing			Mean difference (95% CI)	Mean difference (95% CI)
High	178/1728 (10.3)	1550/1728 (89.7)	1.83 (1.17 to 2.49)	2.03 (1.45 to 2.61)
Low	161/2478 (6.5)	2317/2478 (93.5)	[Reference]	[Reference]
CBCL externalizing			Mean difference (95% CI)	Mean difference (95% CI)
High	58/1728 (3.4)	1670/1728 (96.6)	1.71 (1.15 to 2.28)	0.94 (0.45 to 1.43)
Low	50/2478 (2.0)	2428/2478 (98.0)	[Reference]	[Reference]





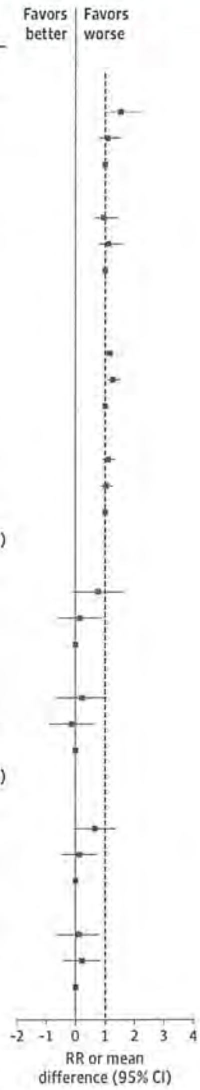
Dashed vertical line at x = 1 represents the reference for risk ratios (RRs). Solid vertical line at x = 0 represents the reference for mean differences.

[a] See descriptions of suicidal behaviors, suicidal ideation, and Child Behavior Checklist (CBCL) internalizing and externalizing scores in footnotes b-d of the Table. Participants with CBCL internalizing and externalizing T scores ≥65 are shown in the "With outcome" column as these scores are considered to indicate clinically elevated symptoms. Exposure categories were dummy coded (low, increasing, high), with the low-use trajectory as the reference group.

[b] For categorical outcomes (suicidal behaviors and suicidal ideation), Poisson regression was used to estimate RRs and 95% CIs using robust standard errors. For continuous outcomes (internalizing and externalizing symptoms), generalized linear models were used to estimate mean differences with 95% CIs using ordinary standard errors. Unadjusted models included only the addictive use trajectories. Adjusted models also controlled for baseline age; sex; race and ethnicity; parental education, income, and marital status; baseline suicidal ideation and behaviors; and baseline internalizing and externalizing symptoms.

Figure 4. Associations of Baseline Screen Time With Year 4 Follow-Up Suicidal Behaviors, Suicidal Ideation, and Mental Health Outcomes

Outcomes, by baseline screen time[a]	No./total No. (%) With outcome	No./total No. (%) Without outcome	RR or mean difference (95% CI)[b]
Suicidal behaviors			**RR (95% CI)**
Weekday screen time			
High	78/1138 (6.9)	1060/1138 (93.1)	1.53 (1.04 to 2.26)
Moderate	54/1133 (4.8)	1079/1133 (95.2)	1.09 (0.78 to 1.53)
Low	85/1964 (4.3)	1879/1964 (95.7)	1 [Reference]
Weekend screen time			
High	99/1732 (5.7)	1633/1732 (94.3)	0.95 (0.64 to 1.41)
Moderate	65/1265 (5.1)	1200/1265 (94.9)	1.11 (0.79 to 1.58)
Low	53/1238 (4.3)	1185/1238 (95.7)	1 [Reference]
Suicidal ideation			**RR (95% CI)**
Weekday screen time			
High	212/1138 (18.6)	926/1138 (81.4)	1.16 (0.95 to 1.40)
Moderate	227/1133 (20.0)	906/1133 (80.0)	1.26 (1.08 to 1.48)
Low	315/1964 (16.0)	1649/1964 (84.0)	1 [Reference]
Weekend screen time			
High	332/1732 (19.2)	1400/1732 (80.8)	1.10 (0.91 to 1.33)
Moderate	225/1265 (17.8)	1040/1265 (82.2)	1.04 (0.87 to 1.23)
Low	197/1238 (15.9)	1041/1238 (84.1)	1 [Reference]
CBCL internalizing			**Mean difference (95% CI)**
Weekday screen time			
High	106/1130 (9.4)	1024/1130 (90.6)	0.77 (-0.09 to 1.63)
Moderate	84/1123 (7.5)	1039/1123 (92.5)	0.15 (-0.58 to 0.88)
Low	149/1948 (7.6)	1799/1948 (92.4)	[Reference]
Weekend screen time			
High	157/1718 (9.1)	1561/1718 (90.9)	0.22 (-0.62 to 1.06)
Moderate	84/1261 (6.7)	1177/1261 (93.3)	-0.14 (-0.88 to 0.61)
Low	98/1222 (8.0)	1124/1222 (92.0)	[Reference]
CBCL externalizing			**Mean difference (95% CI)**
Weekday screen time			
High	45/1130 (4.0)	1085/1130 (96.0)	0.65 (-0.08 to 1.37)
Moderate	24/1123 (2.1)	1099/1123 (97.9)	0.12 (-0.49 to 0.74)
Low	39/1948 (2.0)	1909/1948 (98.0)	[Reference]
Weekend screen time			
High	54/1718 (3.1)	1664/1718 (96.9)	0.11 (-0.60 to 0.81)
Moderate	28/1261 (2.2)	1233/1261 (97.8)	0.22 (-0.41 to 0.84)
Low	26/1222 (2.1)	1196/1222 (97.9)	[Reference]



Risk estimates from models examining associations between baseline screen time (weekday and weekend) and year 4 outcomes: suicidal behaviors, suicidal ideation, and Child Behavior Checklist (CBCL) internalizing and externalizing symptoms, controlling for demographics, suicidal behaviors, suicidal ideation, and CBCL internalizing and externalizing symptom T scores at baseline. Dashed vertical line at x = 1 represents the reference for risk ratios (RRs). Solid vertical line at x = 0 represents the reference for mean differences.

[a]See descriptions of suicidal behaviors, suicidal ideation, and CBCL internalizing and externalizing T scores in footnotes b-d of the Table. Participants with CBCL internalizing and externalizing T scores ≥65 are shown in the "With outcome" column as these scores are considered to indicate clinically elevated symptoms. Baseline screen time was classified as low (≤2 h/d),[43] moderate (>2 to ≤4 h/d), or high (≥4 h/d).[44] Cutoffs were selected based on existing literature that has linked moderate and high levels of screen time to elevated risks of depressive symptoms, anxiety, and behavioral problems in children and adolescents. Exposure categories were dummy coded (low, high, medium), with low screen time as the reference group.

[b]For categorical outcomes (suicidal behaviors, suicidal ideation), Poisson regression was used to estimate RRs and 95% CIs using robust standard errors. For continuous outcomes (internalizing and externalizing symptoms), generalized linear models were used to estimate mean differences with 95% CIs using ordinary standard errors.

the use of a large, population-based longitudinal sample and comprehensive, platform-specific assessment of addictive use trajectories. Previous studies, mostly cross-sectional and measuring only total screen time, have reported associations between more screen time and poorer mental health.[4,10,45,46] The current study's findings align with prior studies observing associations between addictive screen use and psychiatric symptoms at single time points.[47,48] This study adds substantially to existing knowledge by examining longitudinal trajectories and their associations with long-term outcomes.

For both social media and mobile phones, addictive use trajectories followed 3 different patterns, and a substantial proportion of youths had addictive use trajectories that increased over the 4 years of observation, starting at age 10

years. These increasing addictive use patterns, which would not have been predicted based on baseline assessments alone, were associated with elevated risks of suicidal behaviors and ideation. This underscores the potential importance of repeated assessment of addictive use of social media and mobile phones among children entering adolescence. In contrast, video game addictive use followed 2 trajectories, high and low, which were stable over time, potentially allowing earlier identification of risk without repeated assessment.

One key finding was that total screen time was not associated with suicide-related or mental health outcomes, nor did it alter the strength or direction of associations between addictive use trajectories and these outcomes. This underscores the importance of treating time spent and addictive use as separate constructs when examining associations with suicide-related and mental health outcomes.[15]

These findings suggest that focusing future research or interventions on addictive screen use might hold more promise than focusing on total screen time, which may unnecessarily involve low-risk youths. Future studies could evaluate whether monitoring addictive screen use is useful to identify higher-risk youths in clinical practice. Future research could also evaluate interventions that address the addictive aspect of screen use and prevention approaches targeting higher-risk subgroups of children and adolescents.[49,50]

Limitations

There are limitations. First, the observational nature of this study precludes establishing that addictive use trajectories cause the outcomes studied, although the longitudinal design mitigates concerns about reverse causality. Second, reliance on self-reported data may introduce recall and social desirability biases.[20,51] This analysis used weighted confirmatory factor analysis scores for quantifying addictive use, confirming their construct validity, and personal estimates of screen use. Still, future studies should consider incorporating objective measures, such as passive digital monitoring. Third, parent-reported CBCL measures may underestimate mental health conditions. Fourth, the COVID-19 pandemic may have influenced screen time,[10] but sensitivity analyses demonstrated consistent findings (eAppendix 5 in Supplement 1). Fifth, the ABCD Study did not assess multitasking across screen platforms, so it is not possible to tell how measurement of multitasking would have affected these findings. Sixth, not all of the participants in the ABCD Study had year 4 follow-up data available at the time of this study; future analyses should seek to replicate results when these data are available. Finally, these analyses did not include psychosocial and behavioral factors such as bullying,[52] adverse childhood experiences,[53,54] parental monitoring,[55,56] sleep disturbances,[57] stress,[58] social isolation,[49] and social determinants of health (eg, neighborhood and school contexts).[59,60] Future studies should examine potential interactions and mediating relationships among these factors, addictive use trajectories, and mental health outcomes.

Conclusions

High or increasing trajectories of addictive use of social media, mobile phones, or video games were common in early adolescence and were associated with suicide-related and mental health outcomes. Addictive screen use trajectories warrant further study regarding potential use for clinical evaluation of risk and for the design and testing of interventions to improve youth mental health.

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Original Investigation | Pediatrics

Social Media Use and Depressive Symptoms During Early Adolescence

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Abstract

IMPORTANCE In 2023, the US Surgeon General issued the Advisory on Social Media and Youth Mental Health, identifying critical research gaps that preclude evidence-based guidance given that most studies of social media and mental health have been cross-sectional rather than longitudinal and have focused on young adults or older adolescents rather than on younger adolescents.

OBJECTIVE To evaluate longitudinal associations between social media use (time spent on social media) and depressive symptoms across 4 annual waves spanning a 3-year follow-up period from late childhood to early adolescence.

DESIGN, SETTING, AND PARTICIPANTS In this prospective cohort study using data from the Adolescent Brain Cognitive Development Study across 21 study sites from October 2016 to October 2018, children aged 9 to 10 years at baseline were assessed across 4 waves (baseline, year 1, year 2, and year 3), with year-3 follow-up through 2022. Sample sizes varied across waves and measures due to attrition and missing data. Analyses retained all available data at each wave. Data were analyzed from January 2024 to March 2025.

EXPOSURES Self-reported time spent on social media at baseline to 3-year follow-up.

MAIN OUTCOMES AND MEASURES Reciprocal associations between social media use and depressive symptoms (Child Behavior Checklist) at baseline and at 1, 2, and 3 years of follow-up were assessed using longitudinal, cross-lagged structural equation panel models. Covariates included sex, race and ethnicity, household income, and parental educational level.

RESULTS At baseline, the sample included 11 876 participants (mean [SD] age, 9.9 [0.6] years), of whom 6196 (52.2%) were male. After adjusting for stable between-person differences and covariates, within-person increases in social media use above the person-level mean were associated with elevated depressive symptoms from year 1 to year 2 (β, 0.07; 95% CI, 0.01-0.12; *P* = .01) and from year 2 to year 3 (β, 0.09; 95% CI, 0.04-0.14; *P* < .001), whereas depressive symptoms were not associated with subsequent social media use at any interval. The final random-intercept cross-lagged panel model demonstrated a good fit (comparative fit index, 0.977; Tucker-Lewis index, 0.968; root mean square error of approximation, 0.031 [90% CI, 0.029-0.033]). Between-person differences in social media use were not associated with depressive symptoms (β, −0.01; 95% CI, −0.04 to 0.02; *P* = .46) after accounting for demographic and family-level factors.

CONCLUSIONS AND RELEVANCE In this cohort study of 11 876 children and adolescents, reporting higher than person-level mean social media use in years 1 and 2 after baseline was associated with greater depressive symptoms in the subsequent year. The findings suggest that clinicians should provide anticipatory guidance regarding social media use for young adolescents and their parents.

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Key Points

Question Are there within-person associations between social media use (time) and depressive symptoms across early adolescence?

Findings In this cohort study of 11 876 children and adolescents, within-person increases in social media use during early adolescence were prospectively associated with greater depressive symptoms 1 year later, whereas depressive symptoms were not associated with later social media use.

Meaning The findings suggest that more time spent on social media during early adolescence may contribute to increased depressive symptoms over time.

+ Supplemental content

Author affiliations and article information are listed at the end of this article.

Introduction

Social media use among adolescents has risen sharply in recent years, raising concerns about its impact on mental health.[1] In 2021, 42% of adolescents reported persistent feelings of sadness or hopelessness, an increase of 50% from 2011.[2] Although correlations between social media use and depressive symptoms have been previously identified, the directionality of this relationship remains unclear.[3-9] In 2023, the US Surgeon General issued the Advisory on Social Media and Youth Mental Health,[10] calling for longitudinal research, as most prior studies have been cross-sectional and were therefore unable to determine temporality, directionality, or within-person changes.[3-9] Disentangling whether social media use contributes to or is a reflection of preexisting distress is critical for guiding evidence-based interventions and policy decisions.

Building on these concerns, the Differential Susceptibility to Media Effects Model (DSMM)[11] provides a guiding framework for understanding the relationship between social media use and adolescent mental health. The DSMM posits that media effects are not uniform but depend on dispositional, developmental, and sociocultural factors, which in adolescence may include heightened cognitive and emotional reactivity.[12,13] These sensitivities make adolescence a critical period of vulnerability during which social media exposure may have lasting implications for mental health.[14] Social media use may also play a bidirectional role; it can influence future mood states while also being shaped by preexisting depressive symptoms, potentially creating reinforcing cycles of use and distress.[15] By applying the DSMM to examine within-person changes over time,[16] this study aimed to identify whether there are bidirectional associations between social media use and depressive symptoms in early adolescence. Of note, the few existing longitudinal studies on social media and mental health in adolescents have reported mixed findings,[17] and bidirectional relationships remain understudied.

To address this gap, we leveraged data from the Adolescent Brain Cognitive Development (ABCD) Study, an ongoing national prospective cohort study that tracks participants over multiple time points.[18,19] This design enabled us to explore individual trajectories and within-person variability in the association between social media use and depressive symptoms. The design also accounted for autoregressive effects and allowed us to explore the stability of social media use and depressive symptoms over time. We hypothesized that social media use and depressive symptoms in early adolescence would exhibit bidirectional within-person associations over time.

Methods

Study Population

In this cohort study, we conducted analyses of data from baseline to year-3 follow-up of the ABCD Study (5.1 release). The ABCD Study is the largest longitudinal study of adolescent health, brain, and cognitive development in the US. It recruited children aged 9 to 10 years from 21 sites from October 2016 October 2018 (baseline). Participants were assessed across 4 waves (baseline, year 1, year 2, and year 3), with year-3 follow-up through 2022. Specifically, the repeated assessments allowed for a clearer examination of potential directionality—whether changes in social media use preceded shifts in depressive symptoms or vice versa (**Figure 1**). Sample sizes varied across waves and measures due to attrition and missing data. Analyses retained all available data at each wave. The ABCD Study sample, recruitment, protocol, and measures were reported previously[20] and are further described in the eMethods in Supplement 1. Centralized institutional review board approval for the ABCD Study was received from the University of California, San Diego; written assent was obtained from the study participants, and written consent was obtained from their parents or guardians. The current study was a secondary analysis of deidentified ABCD Study and thus did not require additional approval or assent and consent. The current study followed the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) reporting guideline for cohort studies.

Measures

Social Media Use

Social media use was defined for this analysis as time spent on social media daily and was assessed using the ABCD Youth Screen Time Survey administered each year.[21] Adolescents responded to questions about the number of hours and minutes per weekday and weekend day they spent engaging with social media. The total time spent on social media was calculated as the weighted sum: [(weekday mean × 5) + (weekend mean × 2)]/7. Weighted mean social media use was reported as a continuous variable, representing the mean daily time spent (in hours).

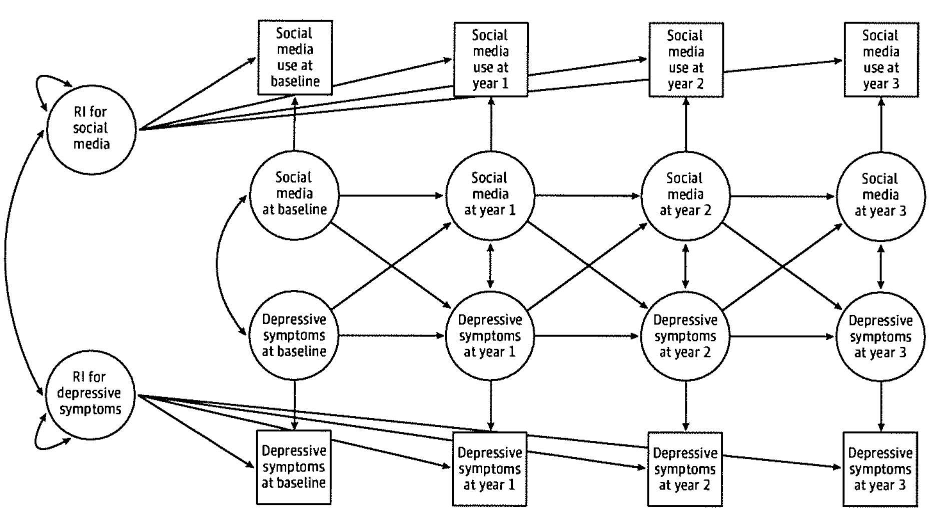
Depressive Symptoms

Depressive symptoms were assessed using the validated Child Behavior Checklist (CBCL) depressive problems score (from the *Diagnostic and Statistical Manual of Mental Disorders*–oriented scales) each year as reported by the caregiver.[22] The raw score (as opposed to the *t* score) was chosen to capture the full distribution of symptom severity in a community-based sample and to avoid the potential loss of within-person variability over time that may occur when standardizing scores according to age- and gender-based norms. Each raw score reflects the sum of items within the depression-related subscale, with higher values indicating more severe symptoms.

Covariates

Several covariates were included to account for demographic and contextual factors that may be associated with social media use or depressive symptoms, including sex (female, male), race and ethnicity (ascertained by parent or caregiver report; categories were Asian, Black, Hispanic or Latino, Native American, White, or other [no defined groups, although write-ins were allowed]), household income (<$25 000, $25 000-$49 999, $50 000-$74 999, $75 000-$99 999, $100 000-$199 999, and ≥$200 000), and highest parental educational level (high school or less vs college or more). The number of adverse childhood experiences,[23] the parental monitoring scale,[24] family conflict (conflict subscale of the Family Environment Scale[25]), and the study site were also included as covariates (the eMethods in Supplement 1 give further details). All covariates were chosen based on prior literature suggesting their relevance to mental health and digital media behaviors.[26]

Figure 1. Conceptual Random-Intercept (RI) Cross-Lagged Panel Model of Social Media Use and Depressive Symptoms



Statistical Analysis

To examine the reciprocal associations between social media use and depressive symptoms over 4 time points, we fit several longitudinal structural equation models.[27] We first estimated a traditional cross-lagged panel model (CLPM) and then compared it with random-intercept CLPMs (RI-CLPMs). The RI-CLPM is an extension of the traditional CLPM that explicitly separates stable between-person differences from within-person fluctuations over time.[28] By introducing latent random intercepts, the RI-CLPM ensures that each individual's trait-like baseline is accounted for, allowing the cross-lagged paths to focus on how temporary (state-like) deviations in one variable are associated with subsequent deviations in another. This approach is particularly valuable when examining processes that may be confounded by persistent individual differences because it isolates the time-varying relationships within persons.[16] In doing so, the RI-CLPM clarifies whether an association is driven by people who have generally high scores on both constructs and by within-person changes that unfold across measurement occasions. It also enables the estimation of autoregressive and cross-lagged parameters that reflect carryover and spillover effects independent of any overall rank-order stability between participants.

All models were estimated using maximum likelihood with robust SEs (MLR) in the lavaan package[29] in R, version 4.4.2 (R Project for Statistical Computing). MLR accounts for nonnormality and provides robust SEs and a scaled test statistic. Full information maximum likelihood was used to handle missing data on the outcome measures (the eMethods in Supplement 1 provide more detail on missing data). We evaluated model fit using the comparative fit index (CFI), Tucker-Lewis index (TLI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR). We relied on fit criteria indicating good to excellent model fit[30] (eg, CFI ≥0.95, TLI ≥0.95, RMSEA ≤0.06, and SRMR ≤0.08). In accordance with the benchmarks of Orth et al,[31] cross-lagged effect sizes were interpreted as small (β = 0.03), medium (β = 0.07), and large (β = 0.12). Two-sided $P < .05$ was considered significant. Analyses were performed from January 2024 to March 2025.

Table 1. Sociodemographic Characteristics of ABCD Study Participants at Baseline

Characteristic	Participants, No. (%) (N = 11 876)
Sex	
Female	5680 (47.8)
Male	6196 (52.2)
Race and ethnicity[a]	
Asian	709 (6.0)
Black	2392 (20.1)
Hispanic or Latino	2027 (17.0)
Native American	410 (3.4)
White	6166 (51.9)
Other	171 (1.4)
Household income, $	
≤24 999	1633 (13.8)
25 000-49 999	1588 (13.4)
50 000-74 999	1498 (12.6)
75 000-99 999	1570 (13.2)
100 000-199 999	3311 (27.9)
≥200 000	1250 (10.5)
Parent's highest educational level	
College or more	2039 (17.2)
High school or less	9799 (82.8)

Abbreviation: ABCD, Adolescent Brain Cognitive Development.

[a] Reported by the parent and/or caregiver of the participant. The "other" category had no specific racial or ethnic groups defined, although write-ins were allowed.

Results

Sociodemographic characteristics of the analytic sample after excluding participants with missing baseline data for age or sex assigned at birth (N = 11 876) are presented in **Table 1**. A total of 5680 participants (47.8%) were female, 6196 (52.2%) were male, and the mean (SD) age at baseline was 9.9 (0.6) years. In all, 709 participants (6.0%) were Asian; 2392 (20.1%), Black; 2027 (17.0%), Hispanic or Latino; 410 (3.4%), Native American; 6166 (51.9%), White; and 171 (1.4%), other race and ethnicity. **Table 2** shows descriptive statistics and 0-order correlations for the untransformed social media use variables and the CBCL depression raw scores across waves; descriptive indices (mean, SD, and range) suggested an overall increase in mean daily social media use from baseline to year 3 and a modest increase in mean depressive symptom scores.

To examine the reciprocal associations among social media use and depressive symptoms over time and to concurrently partition stable, between-person differences from within-person fluctuations, we estimated 3 alternative longitudinal structural equation models. Model comparisons were conducted in a sequential manner and based on standard global fit indices.[30] Following Chen's[32] recommended cutoff criteria for fit indices (eg, CFI ≥0.95, RMSEA ≤0.06, change in CFI ≤0.01, and change in RMSEA ≤0.015), we evaluated whether each model demonstrated good fit and whether differences in fit between nested models were meaningful. First, we estimated the traditional CLPM, which does not partition stable between-person variance and yielded a poor fit (CFI, 0.917; TLI, 0.807; RMSEA, 0.132 [90% CI, 0.127-0.137]; SRMR, 0.065).

Next, we evaluated the constrained RI-CLPM, which incorporates latent random intercepts to capture trait-like differences and imposes equality constraints on the cross-lagged paths across time. The constrained model provided markedly improved fit indices (CFI, 0.966; TLI, 0.957; RMSEA, 0.036 [90% CI, 0.034-0.038]; SRMR, 0.027). Compared with the traditional CLPM, the constrained

RI-CLPM showed improved model fit (change in CFI, −0.049; change in RMSEA, 0.096). In addition, we estimated the unconstrained RI-CLPM, which allowed the cross-lagged parameters to vary freely across time. This model showed further improvement in fit (CFI, 0.977; TLI, 0.968; RMSEA, 0.031 [90% CI, 0.029-0.033]; SRMR, 0.022). Compared with the constrained RI-CLPM, the unconstrained version improved model fit modestly (change in CFI, 0.011; change in RMSEA, −0.005). On the basis of these comparisons and given the theoretical merit of allowing time-specific associations,[14] we retained the unconstrained RI-CLPM as our final model (eTable 1 in Supplement 1). In the unconstrained RI-CLPM, social media use and depressive symptoms were modeled across the 4 waves (baseline, year 1, year 2, and year 3), controlling for between-person variance and the covariates listed in the Methods.

Between-Person Association

eTable 2 in Supplement 1 displays the standardized estimates for fixed covariates of both social media use and depressive symptoms within the final model. There were no between-person associations between depressive symptoms and social media use, as evidenced by the covariance between the latent random intercepts (β, −0.01; 95% CI, −0.04 to 0.02; $P = .46$). This suggests that adolescents with consistently high (or low) social media use were not necessarily the same adolescents with consistently high (or low) depressive symptoms after accounting for demographic and familial factors and within-person estimates.

Within-Person Associations

The time-varying within-person variables were modeled by estimating both autoregressive and cross-lagged paths among the residuals of the observed indicators (**Figure 2** and eTable 3 in Supplement 1). Autoregressive effect sizes were significant for both constructs. Social media use exhibited strong temporal continuity, with an autoregressive coefficient (β) of 0.21 (95% CI, 0.16-0.25; $P < .001$) from baseline to year 1, 0.24 (95% CI, 0.20-0.27; $P < .001$) from year 1 to year 2, and 0.35 (95% CI, 0.32-0.38; $P < .001$) from year 2 to year 3. Depressive symptoms also showed stability, with autoregressive coefficients of 0.17 (95% CI, 0.14-0.20; $P < .001$) from baseline to year 1, 0.18 (95% CI, 0.14-0.21; $P < .001$) from year 1 to year 2, and 0.27 (95% CI, 0.24-0.31; $P < .001$) from year 2 to year 3. Within-wave residual covariance was modeled to assess contemporaneous associations. At year 3, the standardized residual covariance between social media use and depressive symptoms was 0.07 (95% CI, 0.03-0.10; $P < .001$), meaning that individuals reporting

Table 2. Descriptive Statistics and 0-Order Correlations of Key Variables of Social Media Use, Depressive Symptoms, and Covariates Across Baseline and 3 Follow-Up Years

	r											
Variable	1	2	3	4	5	6	7	8	9	10	Participants, No.	Mean value (SD)[a]
1. Social media use, baseline											11 832	0.12 (0.42)
2. Social media use, year 1	0.37										11 175	0.22 (0.60)
3. Social media use, year 2	0.28	0.44									10 370	0.68 (1.54)
4. Social media use, year 3	0.24	0.38	0.56								10 301	1.21 (2.05)
5. Depressive symptoms, baseline	0.03	0.03	0.00	0.00							11 859	1.27 (2.01)
6. Depressive symptoms, year 1	0.03	0.02	0.01	0.01	0.64						11 199	1.39 (2.19)
7. Depressive symptoms, year 2	0.03	0.04	0.05	0.04	0.55	0.62					10 895	1.50 (2.30)
8. Depressive symptoms, year 3	0.03	0.05	0.05	0.06	0.47	0.55	0.63				10 093	1.69 (2.52)
9. Adverse childhood experiences	0.08	0.06	0.06	0.07	0.20	0.18	0.16	0.16			11 865	1.71 (1.59)
10. Parental media monitoring	−0.01	0.02	0.03	0.02	−0.09	−0.10	−0.08	−0.07	−0.14		11 846	4.38 (0.52)
11. Family conflict	0.09	0.04	0.04	0.04	0.11	0.11	0.08	0.07	0.22	−0.24	11 843	2.05 (1.95)

[a] Variables 1 through 4 are hours per day and were transformed in the final analytic model because the first 2 years were reported in ordinal categories while the last 2 were reported in continuous hours (0-24). Variables 6 through 11 are scores (details of scores are given in the Depressive Symptoms subsection of the Methods section and the eMethods in Supplement 1).

social media use higher than the person-level mean at that wave also tended to have depressive symptoms higher than the person-level mean.

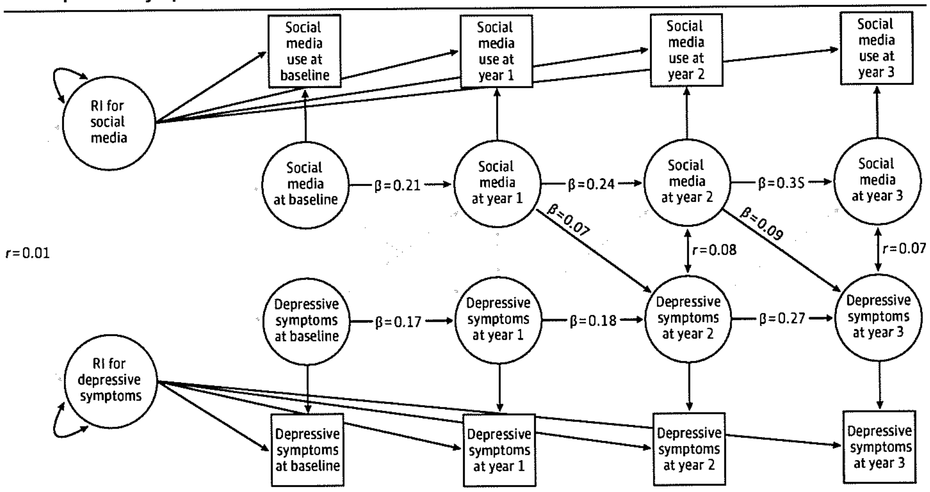
The cross-lagged paths, reflecting how deviations from an individual's expected level on one variable are associated with subsequent deviations on the other, revealed no association between depressive symptoms at baseline and social media use in year 1 (β, 0.00; 95% CI, −0.01 to 0.02; *P* = .46) or between social media use at baseline and depressive symptoms in year 1 (β, 0.03; 95% CI, −0.02 to 0.09; *P* = .19). However, significant cross-lagged associations emerged in subsequent waves. Specifically, from year 1 to year 2, social media use higher than the person-level mean in year 1 was associated with greater depressive symptoms in year 2 (β, 0.07; 95% CI, 0.01-0.12; *P* = .01; medium effect size). This pattern continued from year 2 to year 3, in which social media use higher than the person-level mean in year 2 was positively associated with greater depressive symptoms in year 3 (β, 0.09; 95% CI, 0.04-0.14; *P* < .001; medium effect size). There were no cross-lagged associations between depressive symptoms and later social media use at either interval (eg, year 1 depressive symptoms and year 2 social media use: β, 0.00 [95% CI, −0.007 to 0.01]; *P* = .65; year 2 depressive symptoms and year 3 social media use: (β, 0.00 [95% CI, −0.003 to 0.02]; *P* = .18).

Discussion

In this cohort study of children and adolescents aged 9 to 12 years in the US, we found that there was a longitudinal association between increases in social media use and subsequent depressive symptoms at the within-person level. These findings provide initial evidence of temporal ordering and could suggest that social media use is a potential contributing factor to adolescent depressive symptoms rather than merely a correlate or consequence of such symptoms. Our findings are consistent with prior studies that have found associations between social media use and depression.[33-35] In addition, a meta-analysis of 21 cross-sectional and 5 longitudinal studies found that there was a linear dose-response association between social media use and depression, further suggesting that social media use may be a risk factor for depression.[36]

Only a limited number of studies have assessed bidirectional longitudinal associations between social media use and depression in adolescents, with mixed findings.[37-39] One Australian study of individuals aged 10 to 17 years used the RI-CLPM to analyze data from 2013 to 2015 and found no significant cross-lagged associations between social media use and depression.[38] A Dutch study of data from 2016 to 2018 (mean [SD] participant age of 13.1 [0.8] years) using the RI-CLPM found a unidirectional association between problematic social media use and decreased mental health a year

Figure 2. Results of Random-Intercept (RI) Cross-Lagged Panel Model of Social Media Use and Depressive Symptoms in the Adolescent Brain Cognitive Development Study



Black lines represent statistically significant cross-lagged and autoregressive paths and gray lines, nonsignificant paths.

later but not vice versa.[39] However, that study found no longitudinal associations between social media use intensity (eg, frequency of viewing, messaging) and mental health in either direction.[39] In contrast, our study found that more time spent on social media, conceptually close to the Dutch study's measure of intensity, was associated with later depressive symptoms. Potential reasons for the differing findings could include variations in the periods (adolescent social media use has increased significantly in the past 15 years), age ranges (the analytic cohort in our study was limited to individuals aged 9 to 12 years), and country (US, Australia, and the Netherlands).

These findings can be interpreted within the context of the DSMM,[11] which posits that some adolescents may be more susceptible to negative media effects due to dispositional (eg, personality, self-esteem), developmental (eg, age), and social-contextual factors (eg, family conflict). Differential susceptibilities may also explain why some social media may be beneficial for certain individuals while detrimental to others. In later waves of our study (particularly year 3), adolescents who reported social media use higher than the person-level mean also showed depressive symptoms higher than the person-level mean in the same wave. The contemporaneous associations suggest that immediate factors (eg, negative peer social interactions, family conflict) may coincide with or amplify concurrent distress.

The present study's findings have implications for clinical practice and health policy. When interpreting our findings within the context of the DSMM,[11] interventions targeted at addressing developmental and social-contextual factors that may be associated with the negative effects of social media among adolescents could be considered. In particular, given that age is a likely developmental factor associated with these negative outcomes, early detection of and intervention for social media use are important. Furthermore, although our findings suggest that there is a unidirectional association between social media use and depression, with increases in social media use associated with depressive symptoms through subsequent years, prior research on adolescents, especially those with depressive symptoms, has shown that they can shift from maladaptive to more positive patterns of social media use when they become aware of its impact on their mood.[40] Specifically, qualitative interviews with treatment-seeking adolescents with depression revealed that over time, many adjusted their social media behaviors, reducing stress-related posting, avoiding triggering content, and using social media more intentionally to connect with supportive peers.[41] Interventions that promote mindful, purpose-driven social media use, such as encouraging adolescents to prioritize social connection,[41] may help mitigate negative outcomes and support better mental health.

Clinicians should consider inquiring about social media use among children and adolescents, particularly those younger than the recommended age limits (the minimum age requirement for most social media platforms is 13 years), and providing anticipatory guidance as needed. Professional organizations, such as the American Academy of Pediatrics, could refine guidelines on social media use and emphasize the importance of family media plans and intentional social media use.

Strengths and Limitations

The strengths and limitations of this study should be noted. Our study adds to knowledge in the field of adolescent health and communication science by examining longitudinal associations between social media use and depressive symptoms over 4 years, whereas most previous studies were cross-sectional. In addition, strengths include the analysis of a large, demographically diverse, contemporary sample of children and adolescents in the US. Limitations include the observational design of the study, leading to susceptibility to residual and unmeasured confounders despite adjustment for potential confounders, as well as reporting, recall, and social desirability bias.[42]

Conclusions

In this cohort study of participants enrolled in the ABCD Study at age 9 or 10 years, higher person-level social media use in years 1 and 2 was associated with greater depressive symptoms in years 2 and 3. These findings suggest that more time spent on social media during early adolescence may contribute to increased depressive symptoms over time. Future studies could examine whether social media use is

linked to heightened depressive symptoms by examining short-term shifts in cognitive (eg, negative self-talk, social comparison, or rumination) and excitative (eg, physiological arousal or stress) states, both of which are outlined as mediators in the DSMM.[11] Given that these states may fluctuate over days, weeks, or seasons, more intensive within-person designs (eg, daily diaries, ecological momentary assessment, and passive mobile sensing via smartphone) may offer a more precise understanding of these processes compared with annual assessments. Future research should also continue to examine the prospective relationships between social media and mental health outcomes as the ABCD Study cohort ages to middle and late adolescence as well as aim to examine the mechanisms underlying these associations.

ARTICLE INFORMATION

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Author Contributions: Dr Nagata had full access to all of the data in the study and takes responsibility for the integrity of the data and the accuracy of the data analysis.

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SUPPLEMENT 1.

eMethods. Study Design, Sample, Missing Data, Model Comparison and Construction, and Fixed Covariates
eTable 1. Model Fit Indices for Traditional, Constrained, and Unconstrained Random-Intercept Cross-Lagged Panel Models
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Data Sharing Statement

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EMPIRICAL RESEARCH

Suicide Risk in Emerging Adulthood: Associations with Screen Time over 10 years

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Abstract

Suicide rates have increased over the past decade, and screen media (and social media in particular) are often blamed for this marked increase. However, there is little longitudinal research on this topic. The current study examined the link between various types of screen media use over a 10-year period (from adolescence to emerging adulthood) to suicide risk in emerging adulthood. Participants included 500 adolescents (51% female) who were first surveyed in 2009, when they were an average of 13.82 years old (range 12-15 years). For girls, a high level of social media or television use in early adolescence followed by a marked increase over time was most predictive of suicide risk in emerging adulthood. Additionally, video game use that increased over time was also associated with a higher risk for developing suicide risk for girls. A passive sensing measurement was also included at the final wave of data collection to obtain a more accurate and complete picture of phone use in particular. The use of entertainment apps was risky for girls while reading apps were risky for boys. Additionally, video game use (for boys) was associated with suicide risk when cyberbullying was also high. Identifying nonnormative patterns of media during adolescence may be instructive in terms of suicide prevention efforts.

Keywords Suicide · Media · Longitudinal · Video game · Social media · Passive sensing

Introduction

Suicide is currently the 10th leading cause of death in the United States and the second leading cause for people ages 10–34 (Heron 2019) and has been increasing over the past decade (American Foundation for Suicide Prevention, n.d.). Smartphone and social media usage have also been increasing. A nationally representative sample of United States adolescents revealed that by age 12, a majority of kids (69%) own a smartphone and by age 18, 91% of teens own a smartphone (Rideout and Robb 2019). Many reputable organizations have correlated the rising trends of suicide and smartphone use, accrediting the rise in suicide to smartphone use in general and social media use in particular. In the past two years, NBC, ABC, CBS, Fox, NPR, Psychology Today, and the Mayo Clinic, among other organizations, have all hosted articles subscribing to or questioning this theory (Chuck 2017; ABC News 2017; CBC News 2017; Fox News 2017; Neighmond 2019; Balzer 2019). After so much back and forth, one question remains: Does media contribute to the increase in suicide? The current study examines the association between various types of media use over a 10-year period (beginning in early adolescence) and suicide risk during emerging adulthood. This study specifically examines television use, video games, cell phone use, and social media use as these types of media are most often used by youth today. Additionally, in the final year of the study, passive sensing technology was used to gain a broader understanding of how phone use might relate to suicide risk.

Media and Mental Health

A host of research has examined the impact of media use on mental health, though far fewer studies have examined suicide specifically. A number of studies find that screen

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time in general is related to direct markers of mental health, including depression and anxiety (e.g., Twenge et al. 2018; Viner et al. 2019), and indirect markers such as sleep disturbances, including decreased quantity and quality of sleep (e.g., Tandon et al. 2020; Twenge et al. 2019). Increased social media use often leads to symptoms of depression and anxiety, fear of missing out (FoMo), and loneliness (Barry et al. 2017). Some researchers suggest that social media use builds weaker relationships between people (Twenge 2013) than the potentially stronger relationships face-to-face interaction can provide. However, this relationship may be more nuanced than straightforward, as most adolescents feel that social media allows them to feel more connected with their peers (Nesi 2020).

Other research has found no link between screen time and mental health. For example, a recent meta-analysis found that the association tended to be weak or tenuous at best (Huang 2018). Other longitudinal research has found that there is no long-term association between social media time and depression or anxiety (Coyne et al. 2020). Recent research explains that how individuals use social media is more important than how much time they spend on a social media site (Berryman et al. 2018), which may be the cause of mixed findings. Indeed, positive social media use (such as authentic self-presentation or active use) is linked with positive well-being in social media users (Grieve and Watkinson 2016). There has also been significant research on cell phone use for mental health information systems (MHIS), which use cell phones as a conduit for treating patients with depression (Wahle et al. 2017). This system has indicated that cell phone usage might not all be damaging but could have positive effects on the mental and emotional health of individuals (Anstey Watkins et al. 2018).

Suicide and Media

There has been much less research on the impact of media on suicide risk specifically, even though suicide rates are rising (American Foundation for Suicide Prevention, n.d.). The majority of research on this topic focuses on suicide and media reporting (e.g., Niederkrotenthaler et al. 2020). As online social networks have increased in popularity and acceptance, individuals considering suicide have expressed suicidal ideation on social media either by exhibiting symptoms of mental disorders, which play a contributing role in suicidal ideation, or by explicitly stating suicidal desires (Grant et al. 2018).

Limited research has been dedicated to the impact of media use on suicide. A few studies have found that time spent using media is correlated with suicide risk (e.g., Memon et al. 2018), although some suggest this finding may be because depression, which is commonly linked with suicide, predicts time on social media and not necessarily the other way around (Heffer et al. 2019). A bidirectional relationship could exist, as many have found increased feelings of loneliness from time spent with screens (e.g., Song et al. 2014) and a lack of emotional closeness with peers, which is difficult to replicate electronically (e.g., Sherman et al. 2013). The association between media use and suicide might be stronger in girls. For example, research in general finds a stronger link between screen time and internalizing symptoms (like depression and anxiety) for girls compared to boys (Memon et al. 2018; Nesi and Prinstein 2015; Viner et al. 2019). Very little research has examined gender differences in regard to screen time and suicide. However, research by Twenge et al. (2018) found that time spent using new media was associated with suicide-related outcomes, and the relationship was stronger for adolescent girls compared to boys. This may be because girls tend to be more finely attuned to interpersonal stressors and are more likely to internalize these stressors with emotional distress (Gore and Eckenrode 1996; Rudolph 2002). There are many opportunities for interpersonal stressors, particularly in social media, thus girls may experience these stressors differently and more acutely than boys.

Social media use in particular has also been described as a risk factor in suicide attempts. For example, a recent review describes nine studies (all cross sectional) that find a weak association between social media and suicide risk (Sedgwick et al. 2019), while acknowledging that there is likely substantial heterogeneity in participant responses to social media. A rare longitudinal study found that social media addiction was associated with increased suicide-related outcomes one year later (Brailovskaia et al. 2020).

Other research suggests that media (and social media in particular) may help prevent suicide. A recent meta-analysis (Ferguson 2019) found that there is little evidence of a suicide contagion effect from exposure to suicide-related narratives in fictional characters (such as *Thirteen Reasons Why*). However, the data related to *Thirteen Reasons Why* is complicated. There is evidence that the show has both increased viewers' help-seeking related to suicide and their awareness of ways to attempt suicide (Ayers et al. 2017). Social media can also provide social support for individuals considering suicide, and in fact may reduce the risk of suicide in individuals who take advantage of online suicide support groups (Choudhury and Kiciman 2017). Online social networking can lead suicidal people to seek social support, but it can also lead individuals to greater harm through negative messages on social media (Memon et al. 2018). A few studies have also investigated how new technology, such as passive sensing apps, might be able to accurately predict suicide risk in real time (Allen et al. 2019).

A recent systematic review of the field (Keles et al. 2020) suggests three major methodological problems that occur when examining the link between media and mental health

(and specifically suicide risk in the current study). First, most research is cross-sectional, which limits the ability to determine causality. Second, most research relies on self-report. Third, most research treats subjects as a homogenous population. A person-centered approach is used in the study to account for heterogeneity in participants. This approach assumes heterogeneity in the sample and is used to identify groups of individuals who are similar on a set of characteristics (von Eye and Bergman 2003). Adolescents vary considerably in their use of media, with some patterns being more "risky" for the development of suicide risk than others (Coyne et al. 2019). This approach is rarely taken in the context of suicide and it may be that a particular pattern of media use is most predictive of suicide risk over time.

The Interpersonal Theory of Suicide and Media

The interpersonal theory of suicide (Joiner 2005; Van Orden et al. 2010) offers a useful theoretical perspective on why media use might be related to suicide risk. According to the theory, suicide risk is predicted by two major factors: (1) the desire to die and (2) the acquired capability to enact lethal means (further referenced as *acquired capability*). The theory proposes that the desire to die is influenced by thwarted belongingness (e.g., feelings of loneliness and a lack of stable, caring relationships) and perceived burdensomeness (i.e., believing that oneself is a burden to others). This acquired capability is, in essence, how a person overcomes the innate fear of death, because "dying by suicide is not an easy thing to do" (Van Orden et al. 2010, pg. 590). Acquired capability comes from a reduced fear of death, an elevated tolerance for physical pain, and an exposure to provocative and painful experiences. Media may impact feelings of belongingness, perceptions of burdensomeness, or this acquired capability to enact lethal means.

First, according to the displacement hypothesis (e.g., Lin 1993), the time spent using media might displace meaningful face-to-face interactions with others, and a lack of face-to-face interactions may decrease feelings of belongingness. Second, a variety of social media experiences might increase feelings of thwarted belongingness, including being cyberbullied or excluded online (Brunstein Klomek et al. 2019), having negative experiences with sexting (Medrano et al. 2018) or using media in passive ways with little meaningful interaction with others (Escobar-Viera et al. 2018). Third, media may provide access to experiences that may indirectly increase a person's acquired capability to enact lethal means. For example, there are many painful or provocative media interactions (e.g., watching videos of people die, and getting visual or textual descriptions of suicide attempts) that may reduce a person's innate fear of death and increase their risk of suicide. Fourth, media overuse or addiction may impair the amount of sleep a person gets; inadequate sleep has been shown to increase negative cognitions (which may increase feelings of thwarted belongingness and perceptions of burdensomeness) and increase acquired capability to enact lethal means in a number of ways (e.g., by increasing tolerance for physical pain and reducing fear of death).

While media may provide several modes that increase suicide risk (e.g., being cyberbullied on social media), there is also potential for media to function as a protective mechanism against suicide (e.g., having positive, connective experiences on social media). This protection is likely to happen in two main ways:(1) media might be used to build relationships and increase feelings of belongingness; and (2) media might be used to seek help for negative cognitions or for overall health issues, which in turn reduces acquired capability.

Current Study

Most research on suicide and media are cross-sectional, self-report, and treat participants as a homogenous sample. The major aim of the study is to examine the longitudinal impact of various growth patterns of media use over a 10-year period on suicide risk in emerging adulthood. Additionally, passive sensing technology was used in the final wave of data to examine how various media activities are related to suicide risk cross-sectionally. Theoretically, it may be that developmentally inappropriate patterns of media use might be related to suicide risk. These patterns would include very high and increasing media use over time that may displace or discourage social interaction, increase cyberbullying, or expose adolescents to suicide-related materials online they are not developmentally ready to process. Thus, Hypothesis 1 (longitudinal study) was that a high and increasing pattern of media (particularly social media use) might be related to suicide risk over time, and this would be particularly strong for girls. Hypothesis 2 (cross-sectional) was that time spent on apps that involved social media, games or entertainment, would be related to higher levels of suicide risk, while time spent on apps that involved education, information & reading, or health would be associated with lower levels of risk. Finally, Hypothesis 3 was that time spent specifically on media use might be moderated by factors that decrease belongingness, such as passive use and cyberbullying.

Method (Longitudinal)

Participants and Procedures

The participants for this study were taken from the Flourishing Families Project, which is an ongoing, longitudinal

study of inner family life. This project involves families whose child was between the ages of 10 and 13 (N = 500; 51.6% female) at the beginning of the study. The data from the current study is from Waves 3–11, when media usage was included in data measurement (N = 459 at Wave 3). There was a 70.58% retention rate between all 10 years of data collection in the current paper. At Wave 3, participant children averaged 13.82 (SD = 1.03) years of age, with mothers averaging 43.1 years of age and fathers 45.3 years. Around 67% of children came from a two-parent family, with 33% coming from a single-parent family. Approximately 65% of families were Caucasian, 12% were Black, 19% were multi-ethnic, and 4% were other. In terms of parental education, 61% of mothers and approximately 70% of fathers had a bachelor's degree or higher. Related to yearly family income, 18.2% of families reported making less than $59,000; 28.5% reported income in the $60,000–99,000; 32.1% reported income in the $100,000–149,000; and 21.2% reported making $150,000 or more per year.

Procedure

Participant families were selected from a large northwestern city and interviewed during the first eight months of 2007 for a Wave 1 data sample. Wave 3 (the first year in the current paper) took place in 2009, while Wave 11 took place in 2019. Participants took part in the study once a year each year until Wave 10. Wave 11 took place approximately three years after Wave 10. Families were primarily recruited using a purchased national telephone survey database (Polk Directories/InfoUSA). At that time, this database contained 82 million households across the United States and provided detailed information about each household, including the presence and age of children. Families identified using the Polk Directory were randomly selected from targeted census tracts that mirrored the socioeconomic and racial stratification of reports of local school districts. All families with a child between the ages of 10 and 14 living within target census tracts were deemed eligible to participate in the project. Of the 692 eligible families contacted, 423 agreed to participate, resulting in a 61% response rate. However, the Polk Directory national database was generated using telephone, magazine, and internet subscription reports; as a result, families of lower socio-economic status were under-represented. Therefore, in an attempt to more closely mirror the demographics of the local area, a limited number of families were recruited into the study via other means (e.g., referrals and fliers; $n =$ 77, 15%). By broadening the approach, the socioeconomic diversity of the sample was increased.

All families were contacted directly using a multi-stage recruitment protocol. First, a letter of introduction was sent to potentially eligible families (this step was skipped for the families who responded to fliers). Second, interviewers made home visits and phone calls to confirm eligibility and willingness to participate in the study. Once eligibility and consent were established, interviewers made an appointment to come to the family's home to conduct an assessment interview that included videotaped interactions, as well as questionnaires that were completed in the home for waves 3–5 and then online for waves 6–11 (as children aged out of the home).

Measures

Media use (Waves 3–11)

Participants were asked about their media use during Waves 3 through 11. Participants reported how much time they spent on a typical day watching TV programs (on any device), playing video games (online or offline), talking on a cell phone, texting on a cell phone, and using social networking sites (e.g., Facebook, Instagram, and Twitter). They responded on a 9-point Likert scale (1 = *none*, 2 = *Less than 20 min*, 3 = *31–60 minutes*, 4 = *1–2 h*, 5 = *2–3 h*, 6 = *3–4 h*, 7 = *5–6 h*, 8 = *7–8 h*, 9 = *More than 8 hours*).

Suicide risk (Wave 11)

Participants were administered the Revised Suicidal Behavior Questionnaire (SBQ-R; Osman et al. 2001), which is a questionnaire that asks about past attempts of suicide, frequency of suicidal thoughts, threat of suicide, and the likelihood of dying by suicide. Scores range from 3 to 18, with scores higher than 6 meaning the participant has clinical levels of suicide risk.

Depression (Wave 3)

Depression was assessed at Wave 3 using a 20-item self-report Center for Epidemiological Studies Depression Scale for Children (CES-DC; Weissman et al. 1980). The stem "During the past week" was followed by 20 questions, including "I did not feel like eating, I wasn't very hungry." and "I didn't sleep as well as I usually sleep." Participants rated the items on a 4-point Likert scale (1 = *Not at all*, 2 = *a little*, 3 = *some*, 4 = *A lot*). Suicide risk was not included at the initial wave, so depression symptoms were controlled because the two tend to be positively correlated (e.g., Vázquez et al., 2018).

Analysis Plan

In order to test the hypotheses, the linear and quadratic growth were examined in social media, television use,

Table 1 Means and standard deviations of main variables of the study

	Social Media		Television		Video game		Depression		Suicide risk	
Wave	Male M(SD)	Female M(SD)	Male M(SD)	Female M(SD)	Male M(SD)	Female M(SD)	Male M(SD)	Female M(SD)	Male M(SD)	Female M(SD)
3	2.44 (1.71)	2.81 (1.96)	3.78 (1.89)	3.84 (1.81)	3.35 (1.87)	1.82 (1.21)	1.60 (0.41)	1.06 (0.48)	--	--
4	3.01 (1.81)	3.58 (1.93)	3.57 (1.69)	3.70 (1.65)	3.32 (1.85)	1.72 (1.23)	--	--	--	--
5	3.14 (1.78)	3.82 (2.03)	3.39 (1.60)	3.75 (1.75)	3.35 (1.83)	2.08 (1.70)	--	--	--	--
6	3.18 (1.78)	3.85 (1.89)	3.41 (1.65)	3.79 (1.70)	3.22 (2.02)	1.74 (1.26)	--	--	--	--
7	3.30 (1.81)	4.05 (1.97)	3.25 (1.63)	3.68 (1.82)	3.03 (2.00)	1.69 (1.32)	--	--	--	--
8	3.30 (1.86)	4.04 (1.87)	3.09 (1.60)	3.72 (1.95)	2.87 (1.93)	1.60 (1.28)	--	--	--	--
9	3.16 (1.69)	4.12 (1.83)	3.09 (1.60)	3.49 (1.84)	2.86 (2.01)	1.53 (1.27)	--	--	--	--
10	3.20 (1.64)	4.11 (1.88)	3.07 (1.51)	3.21 (1.73)	2.80 (1.88)	1.63 (1.32)	--	--	--	--
11	3.64 (1.51)	4.21 (1.59)	3.08 (1.40)	3.65 (1.68)	2.92 (1.87)	1.52 (1.19)	--	--	4.60 (4.00)	4.30 (4.03)

Note. M and SD are indicative of mean and standard deviation, respectively

video games, texting, and talking on the phone. A chi-square difference test and an examination of the significant means and variances of the growth parameters were used to determine whether the linear or quadratic model fit the data best. It was elected to retain the quadratic term and import the growth parameters into STATA, where they were used as independent variables. Next, five zero-inflated negative binomial regressions were conducted to analyze the relationship between the growth in media use over time with suicide risk. Depression and age at Wave 3 were used as control variables in the model. A zero-inflated negative binomial regression was fit in STATA. The zero-inflated negative binomial regression estimates two regressions. The inflated estimation predicts a dichotomous outcome of whether or not the participants have zero suicide risk or some suicide risk. For those whose suicide risk is greater than zero, the negative binomial regression predicts their level of suicide risk above zero. Suicide risk was regressed on the intercept, linear slope, and quadratic slope of the media type. Additionally, moderation by biological sex was performed using "#" in STATA, which creates an interaction between two variables. For models with significant growth parameters, margins postestimation commands were used in STATA to determine different levels of suicide risk based on the significant growth parameters.

Results (Longitudinal)

Preliminary Analyses

Means and standard deviations for all the main variables of the study were computed (see Table 1). There was 35% attrition in this study. The logistic regression examined whether the missingness was systematic and found missingness unrelated to biological sex, age, or depression at Wave 3. Because the data were seemingly missing completely at random, it was opted to handle the missingness with multiple imputation (Little et al. 2014).

Main Analyses

Hypothesis 1 was tested with five linear growth models for social media use, television, video games, talking on the phone, and texting computed in Mplus. Next, the quadratic growth models were fit. All the quadratic growth models fit the data better than the linear growth models, as indicated by the CFI, the RMSEA, and significant chi-square difference tests (see Table 2). In addition, each model had at least one significant mean or variance of the quadratic growth parameter, with most having both significant. The growth parameters for these models were imported into STATA and the five negative binomial regression models were computed.

Social media

In the negative binomial part of the analysis (levels of suicide risk for those who report any suicide risk), for girls, the intercept ($\beta = 0.08$, $p = 0.025$) and linear slope ($\beta = 0.68$, $p = 0.015$) of social media use predicted more suicide risk at Wave 11. In other words, for girls who report any levels of suicide risk, the higher the starting point of their social media use and the more rapidly their social media use increased, the greater the suicide risk at Wave 11. Post estimation commands also suggest that adolescents whose social media use at the first wave is 2–3 h or more and increased over time could be at clinical levels of suicide risk (see Fig. 1). There were no significant predictors for boys in either part of the analysis (see Table 3 for all coefficients).

Table 2 Fit information for the linear and quadratic growth models

Model Tested	χ^2	df	$\Delta\chi^2$	Δdf	p	RMSEA	CFI	ΔCFI
Linear								
Social Media	276.44	40	--	--	--	0.11	0.87	--
Television	122.76	40	--	--	--	0.07	0.96	--
Video Games	151.40	40	--	--	--	0.08	0.96	--
Talk	166.65	40	--	--	--	0.08	0.92	--
Text	335.88	40	--	--	--	0.12	0.87	--
Quadratic								
Social Media	152.32	36	124.12	4	<0.001	0.08	0.94	0.07
Television	84.28	36	38.48	4	<0.001	0.05	0.98	0.02
Video Games	101.90	36	49.50	4	<0.001	0.06	0.97	0.01
Talk	135.48	36	31.16	4	<0.001	0.08	0.93	0.01
Text	166.06	36	169.82	4	<0.001	0.09	0.94	0.07

Note. χ^2, df, and Δ, are indicative of chi-square, degrees of freedom, and change, respectively

Television

For girls, the intercept ($\beta = 0.10$, $p = 0.015$), linear slope ($\beta = 0.58$, $p = 0.044$), and quadratic slope ($\beta = 10.05$, $p = 0.006$) of television viewing predicted more suicide risk at Wave 11 in the negative binomial part of the analysis. For girls, the linear slope ($\beta = 2.85$, $p = 0.011$) and the quadratic slope ($\beta = 32.20$, $p = 0.018$) predicted suicide risk in the zero-inflated part of the analysis. The variance of the quadratic slope in the inflation portion of the model was low, creating unstable and unreliable estimates. The quadratic slope was removed from the model, leading to appropriate model parameters. For girls, having a high intercept, a positive slope, and a rapid increase in television watching in the later years was associated with the highest levels of suicide risk. Those who did not accelerate in the later years did not have strong effects (see Fig. 1b).

Video games

For girls, the linear slope ($\beta = 0.07$, $p = 0.033$) and the quadratic slope ($\beta = 8.19$, $p = 0.008$) of video game use predicted suicide risk at Wave 11 in the negative binomial part of the analysis. Girls who accelerated in their video game use more rapidly in the later years (regardless of where they started) were at the highest risk of suicide risk. Girls whose general trend was increasing were also at higher risk than those whose trend was decreasing (see Fig. 1c).

Talk and text

There were no significant associations between any of the talking and texting variables and suicide risk at Wave 11 for the negative binomial or zero-inflated portions of the models.

Sensitivity Analysis

An alternative method of estimation was used as a sensitivity analysis. Zero-inflated negative binomial models were estimated separately for boys and girls rather than using biological sex as a moderator. The results were the same in magnitude and significance for social media, television, and texting. For video games the intercept, linear slope, and quadratic slope also predicted more suicide risk for boys in the negative binomial part of the model. For talking on the phone, the intercept linear slope, and quadratic slope predicted more suicide risk for boys in the negative binomial part of the model.

Method (Cross-Sectional)

Participants and Procedure

Participants for this portion of the study came from a subsample of 281 participants that participated in Wave 11 of the project. Fifty-eight percent of the participants were female, 41% were male and 1 % were other. 80% of the participants were Caucasian, 4% were African American, 4% were Asian, 3% were Hispanic, 6% were mixed, and 3% were other. The average age was 23.3 years (SD = 1.04). For education, 7% of participants had a high school education or less, 54% had some college or were currently enrolled and 38% had a bachelors or higher.

Measures

Suicide risk was measured as described previously. Additional measures are described below.

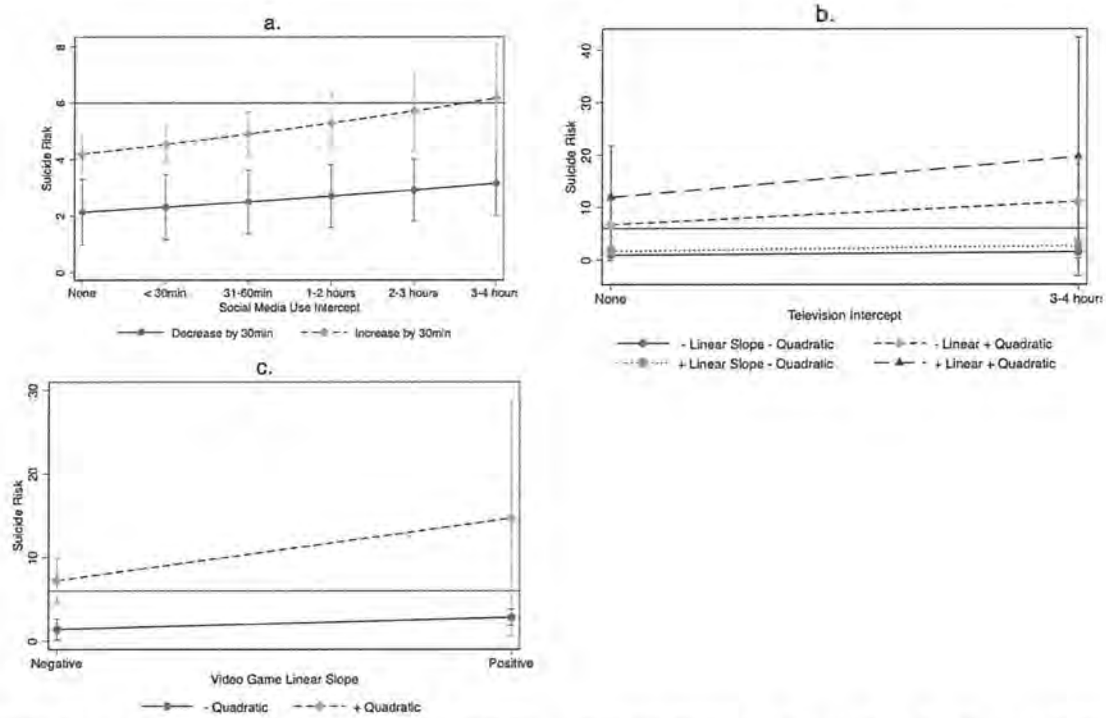

Fig. 1 Margins plots for (**a**) social media use for females, includes intercept and linear slope (**b**) television use for females, includes intercept at min and max, linear and quadratic slope and (**c**) video game use for females includes linear and quadratic slope. The solid horizontal line represents the clinical cutoff of a score of 6 on the suicide risk measure

Passive sensing

Participants downloaded a passive sensing app (Moment for iPhone and Chronicle for Android) on their phones for two weeks. These programs provide an accurate amount of time spent on each cell phone app and is described below. Participants who agreed to and participated in this portion of the study received an additional $25 for participating. Seventy-two percent of the participants had an iPhone and 39% had an Android. The use of passive sensing apps is a relatively new way to measure the actual media use of participants, rather than relying on self-reported items (e.g., Radesky et al. 2020). The data collected from the passive sensing apps were used to compute the daily average of each app on the participants' phones.

Each app was coded into a discrete category. At the time of coding (but after data collection had begun), apple had just released the app "screentime" which automatically assigns a category to each app. These pre-existing categories were utilized to assign each app used in the current study. The categories are creativity, education, entertainment, games, health & fitness, information & reading, productivity & finance, shopping & food, social networking, travel, and utilities. For iPhone apps ($n = 505$), research assistants downloaded each app on a phone, used the app for several minutes and then opened screentime to see which category was assigned. If apps were not assigned a specific category in screentime, they were assigned as "other" (8% of apps). For Android apps ($n = 982$), it was first checked to see if there was an iPhone equivalent, which there was in the majority of cases. If so, the process as described above was used. If the app did not exist in the apple store and if research assistants could not find an equivalent, the information found on the Google Play store was examined to give the app a category. The rating was based on both the description of the app but also the category ascribed (e.g., #7 in games). Some apps could theoretically fit into more than one category, however, for coding ease and parsimony, the categories were mutually exclusive. These apps were coded by multiple coders and 100% consensus was reached for app categorization. Apps that could not be found on the Google Play store or no clear category could be derived were coded as other (15% of Android apps). A list of all apps and categories can be found in the supplementary material.

This process allowed us to go beyond overall screen time and examine the use of specific types of use by using an externally valid and replicable method. It should be noted that existing categories could have been broken into smaller ones (e.g., romantic social networking, work social networking, general social working), or using contextual features of the app (e.g., multi-player vs. single player game).

Table 3 Regression coefficients of social media types predicting suicide risk

	Social Media		Television		Video Games		Texting		Talking	
	NB	ZI	NB	ZI	NB	ZI	NB	ZI	NB	ZI
Age	0.01	0.15	−0.01	0.12	0.01	0.10	0.01	0.09	−0.01	0.16
Depression	0.01	−0.12	0.02	−0.09	0.04	−0.08	0.03	−0.13	0.02	−0.08
Intercept	0.08*/−0.02	0.04/0.05	0.10*/0.01	0.19/−0.01	0.05/0.03	−0.31/−0.11	0.05/−0.05	−0.20/0.13	−0.05/0.13	0.15/0.47
Slope	0.68*/−0.19	1.80/0.03	0.58*/0.29	2.85*/−0.66	0.70*/0.51	−0.79/−0.80	0.51/−0.56	−1.01/0.33	−0.33/0.69	3.30/5.40
Quadratic	4.60/−1.15	14.50/−1.27	10.05*/1.90	32.20*/−10.60	8.18*/3.78	−5.60/−10.12	3.40/−5.60	−9.80/5.90	−4.50/12.23	17.68/43.45

Note. NB is indicative of Negative Binomial and ZI is Zero-inflated. Coefficients before the slash are for females and after are for males (i.e., females/males)

$^*p < 0.05$

However, for parsimony and ease of interpretation, it was elected to utilize the existing screentime categories. Mean scores of the average daily time for each category were computed and used for analysis. The app categories of education, entertainment, games, health & fitness, information & reading, and social networking are examined in the analyses as these apps could theoretically be either risk or protective factors for suicide risk. Based on previous research, it was hypothesized that the use of entertainment, games and social networking apps might be a risk factor and the use of education, health & fitness, and reading & information apps might be a protective factor for suicide risk. For parsimony and power issues, shopping, travel, creativity, productivity, utilities, and other were not included in the main analyses due to lack of theoretical justification. However, models were conducted with these app categories and are included in the online supplementary materials for reader interest.

Cyberbullying and victimization

Cyberbullying and victimization were examined using a 6-item scale based on the cyberbullying and victimization scale by Shapka and Maghsoudi (2017). Participants were asked to indicate how often they engaged in a variety of online activities using a 1 (never) to 5 (very often) scale. There were two subscales. Cyberbullying consisted of three items (e.g., "Post or text a hurtful comment about an online photo or video of somebody else, for example, made fun of how they look?"; $\alpha = 0.52$) and cybervictimization consisted of three items (e.g., "Had something embarrassing or mean posted or re-posted about you online?"; $\alpha = 0.75$).

Sexting

Sexting was measured by a single item, loosely based on a scale created by Rauch and Schanz (2013). Participants were asked to indicate how often they "sent nude or sexy pictures to others (via text, a social media site, etc.)" on a 1 (never) to 5 (very often) scale.

Positive and negative use of media

To capture both positive and negative uses of media, eight items loosely based on Escobar-Viera et al. (2018) were created. There were two subscales: Positive use of media involved using media in more active or connective ways (e.g., "Post something on a social media site" or "Get on social media to feel a sense of connection from others"; $\alpha = 0.74$). Negative use of media involved using media in more passive or destructive ways (e.g., "Scroll through social media without posting anything" or "Compare yourself to others on social media"; $\alpha = 0.74$).

Table 4 Means, standard deviations, for boys and girls, univariate F tests

Variable	Male M(SD)	Female M(SD)	*F*
Suicide risk	5.51 (2.74)	5.47 (3.2)	0.01
Bullied	1.28 (0.43)	1.32 (0.49)	0.50
Positive Reasons For Media Use	2.52 (0.90)	3.13 (0.77)	36.66***
Negative Reasons for Media Use	2.95 (0.88)	3.54 (0.67)	41.13***
Sexting	1.30 (0.57)	1.60 (0.91)	9.27***
Education	0.64 (2.95)	0.99 (6.99)	0.26
Entertainment	31.87 (62.80)	10.04 (20.83)	17.06***
Games	16.44 (48.79)	7.28 (24.12)	4.26*
Health	0.27 (1.21)	0.41 (1.92)	0.46
Reading	13.88 (51.16)	4.24 (15.82)	5.10*
SN	34.35 (47.86)	28.23 (42.67)	1.25

Note. M and SD are used to represent mean and standard deviation, respectively

F represents the test statistic for the univariate difference tests

*$p<0.05$, **$p<0.01$, ***$p<0.001$

Analysis Plan

A Multivariate Analysis of Variance (MANOVA) was conducted to examine differences between girls and boys in suicide risk, the moderators (being bullied, bullying, positive reasons for media use, negative reasons for media use, and sexting), and the app averages. Next, five, two-step hierarchal regressions in STATA. The first step included all the app averages and one of the moderators. The second step included all the interactions between the app means and the moderator. For example, in the model that is moderated by sexting, the first step included the means of the app categories (education, entertainment, games, health & fitness, information & reading, and social networking) as well as sexting. The second step included everything in the first as well as the interactions between sexting and games, sexting, and health, sexting and productivity, sexting and reading, sexting and social networking, and sexting and entertainment. These models were run separately by boys and girls due to the differences in media use and suicide risk by biological sex. To decrease the likelihood of Type 1 error, the cutoff p-value for interactions was adjusted to 0.01.

Results (Cross-Sectional)

Preliminary Results

A Multivariate Analysis of Variance (MANOVA) was conducted to examine differences between boys and girls in suicide risk, the moderators, and the app averages. Box's test was significant: F (66, 1931666.96) = 10.22, $p<0.001$, so Wilk's Lambda was used, which showed that the multivariate effect showed significant sex differences: Wilks l = 0.79, F (11,266) = 6.48, $p<0.001$. An examination of the univariate results revealed significant differences on all moderators except for being bullied and the app categories of entertainment, games, and reading. (see Table 4 for means and F statistics).

Main Results

Hypothesis 2 was examined through a series of hierarchical regression analyses (see Table 5 for all results). Analyses revealed that higher use of reading apps for boys ($\beta=$ 0.28–0.29, $p<0.001$) and entertainment apps for girls ($\beta=0.23$–0.25, $p<0.001$) was related to higher suicide risk in each model.

Interaction effects were then included (see Table 5) to test Hypothesis 3. The model did not converge well when bullying was added as a moderator. This is likely a result of the high skew and possibly low reliability of this variable. Thus, it was elected to drop bullying as a moderator (and just focus on victimization in the bullying context).

There was a significant interaction in the model for time spent playing games and level of victimization for boys only ($\beta=0.27$, $p=0.010$) in that boys who played more games and had higher levels of victimization had the highest suicide risk (see Fig. 2a). Additionally, there was also a significant interaction in the model for time spent using education apps and using social media for negative reasons, again for boys only ($\beta=0.30$, $p=0.008$) in that boys who used more education apps and had higher levels of negative media use had the highest suicide risk (see Fig. 2b).

Sensitivity Analysis

An alternative model was used in the sensitivity analysis. A multiple group path analysis of suicide risk predicting the app categories was estimated in STATA. Suicide risk predicted using more reading apps for boys, and more social networking and entertainment apps for girls.

Discussion

There is much debate concerning the link between media use and suicide, both in the academic world (e.g., Coyne et al. 2020; Twenge et al. 2018) and the popular press (Chuck 2017). However, most research is cross-sectional or self-report, ignoring long-term patterns of media use over time. This 10-year longitudinal study (the longest of its kind

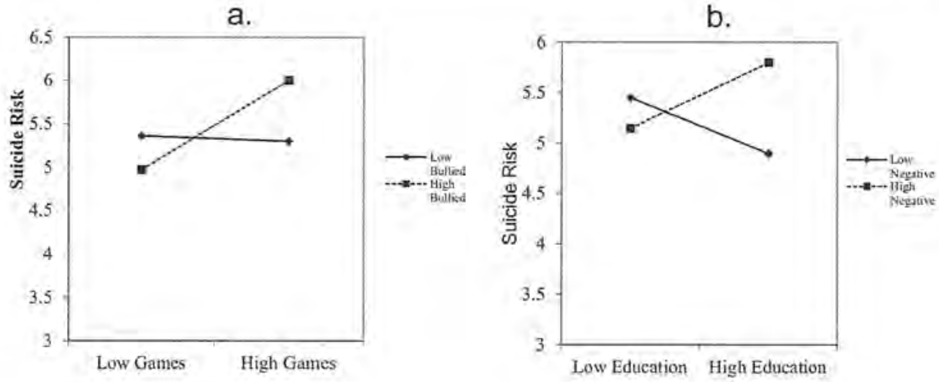

Fig. 2 Interaction plots predicting suicide risk of (**a**) games with bullied for boys and (**b**) education apps and negative reasons for using social media for boys

to the author's knowledge) found that there is some cause for concern as certain types of media patterns over the course of adolescence were related to suicide risk in emerging adulthood, particularly for girls. Additionally, some contextual features (such as being cyberbullied or using social media in negative ways) moderated the results. The specific findings are discussed below, split by the longitudinal and cross-sectional methods.

Longitudinal Results

There was some evidence of significant heterogeneity of media use over time, as related to suicide risk. For girls, various patterns of social media, television, and video games were predictive of suicide risk a decade later. For social media, early and high levels of social media that increased over time was associated with higher levels of suicide risk in emerging adulthood. In other words, these girls had relatively high levels of social media use early in adolescence (around 2–3 hours daily at the starting point) that increased over time. This confirms a number of studies that show that time spent on social media may be a risk factor for suicide, especially for girls (e.g., Memon et al. 2018; Twenge et al. 2018). Our research extends these findings and suggests it is not simply time but very high and increasing levels of time spent on social media that increase suicide risk in emerging adulthood. Using social media does appear to have a number of protective benefits when utilized in positive ways (e.g., Choudhury and Kiciman 2017; Escobar-Viera et al. 2018). However, it may be that a slower and sustained pattern of social media use over time represents a more developmentally appropriate pattern for adolescents to follow, whereas the real risk is very high levels of social media when the child is not developmentally ready for that level of involvement.

A similar pattern was also found for television for girls, with higher early levels and a positive slope presenting the highest risk for suicide risk over time. This finding confirms some longitudinal research specifically on television (Boers et al. 2019). Viewing television is often (though not always) a solitary activity. It may be that viewing high amounts of television may displace early face-to-face interactions with others, which may in turn decrease feelings of belonginess (e.g., Lin 1993).

Finally, increasing levels of videos games tended to be most predictive of suicide risk over time for girls. The high, increasing trajectory likely represents a nonnormative pattern for most adolescent girls. Though many girls like and play video games, this type of pattern is far less common for girls than it is for boys (e.g., Lucas and Sherry 2004). It may also be reflective of a video game addiction, which tends to be related to mental health issues longitudinally (e.g., Coyne et al. 2020), though gaming addiction was not specifically examined in the current study.

Interestingly, there were no longitudinal effects of screen time on suicide risk for boys, at least in the main analysis. Notably, the sensitivity analyses suggested that early and high increasing video game use and time spent talking on the phone might be related to increased suicide risk, though these were not found in the main analysis, so further research is needed here. It may be that the context or content (e.g., Mitchell et al. 2015) of media may be particularly important for boys (as opposed to sheer amount of screen time). It also is possible that suicide risk develops differently for boys and girls, with boys less impacted by screen time. A number of studies have found that screen time (and particularly social media) tends to have a larger impact on mental health for girls (Memon et al. 2018; Nesi and Prinstein 2015; Twenge et al. 2018; Viner et al. 2019). Perhaps screen time leads to different feelings of belongingness or perceived burdensomeness for boys and girls, leading to a differential impact on suicide risk (Joiner 2005). Girls tend to be more sensitive than boys to interpersonal stressors and are more likely to react to these experiences with emotional distress (Gore and Eckenrode 1996; Rudolph 2002). Additionally, girls tend to engage in higher levels of social comparison with others online, which tends to be related to mental health issues (Haferkamp and

Karmer 2011). These links may become particularly apparent when girls are not developmentally ready to handle all the interpersonal stressors that may come with engaging with others in a social media context (whereas boys may be less impacted).

In terms of prevention, it appears that developmentally normative patterns of media use over the course of adolescence may be protective for developing suicide risk over time, especially for girls. Education efforts aimed toward parents and adolescents might focus on healthy and developmentally appropriate use of screens and technology. This type of media literacy is rare in the majority schools beyond a token lesson or two (at least in the United States) but vitally important in this media environment (e.g., Alutaybi et al. 2020). It is hoped that more schools consider these types of programs starting at an early age, which would likely be most effective before adolescents start using social media. It might also be instructive to track adolescent media use over time and then flag for possible intervention those who show nonnormative patterns—particularly if they also show other risk factors related to suicide. Passive sensing apps may be one useful technology to provide this type of data, though there are many privacy concerns to tackle before this approach becomes widespread (Allen et al. 2019).

Cross-sectional Study

The previous results show that differential patterns of various screen time are moderately successful at predicting suicide risk over time, especially for girls. However, there are some significant limitations in these results, as the data are all self-reported and focus on screen time only. The purpose of obtaining this additional data via passive sensing apps was to provide an in-depth and methodologically independent examination of how phone use concurrently relates to suicide risk during emerging adulthood.

For girls, using entertainment apps at high levels was associated with increased suicide risk. This confirmed the longitudinal results, which found that high and increasing levels of television—which is predominantly entertainment—created the highest risk trajectory for girls. Again, this type of use may displace face-to-face time with peers or family, leading to lower levels of belonginess (Lin 1993). The main analyses did not confirm the longitudinal results that time spent using games or social media was associated with higher suicide risk for girls. For games, it may be that games played on consoles (not captured in the passive sensing method) might be more common or more predictive of risk than games played on phones. This finding should be explored with future research. However, the sensitivity analysis suggested that suicide risk predicted higher levels of social media use (as opposed to the converse that was explored in the main analyses). Thus, in the long-term, developmentally inappropriate patterns of social media use might predict suicide risk for girls. However, in the short term, those girls who may be feeling suicidal may turn to social media, perhaps as a coping method or to obtain help. There were no significant moderators for girls.

For boys, time spent on video games was only related to suicide risk for boys when bullying was also high. Video games can have a large social component, with many boys playing games with friends or others online. This can be somewhat protective—for example, Carras et al. (2017) found that high video game use was associated with depression, unless the use was moderated by heavy online social interaction. However, video games can also provide a mechanism for bullying, with 57% of adolescents reporting being bullied while playing online video games, such as receiving death threats, being called names, or being threatened (BBC, 2017). Thus, the context of game play appears to matter more than the sheer amount of time spent playing, at least cross-sectionally.

There were also two findings for boys that were less straightforward. First, using reading apps was associated with increased suicide risk for every model analyzed. Though reading on the whole tends to be related to decreased mental health issues (Boyes et al. 2018), an examination of the apps classified as "information & reading" revealed that many of these apps are news related or more emotionally charged (such as Reddit where there can be some cyberbullying involved). There is some evidence that reading certain types of news outlets tend to be related with a higher endorsement of suicide myths (Till et al. 2018), as some news outlets may provide inaccurate or sensational material around suicide. Additionally, the majority of news articles covering suicide do not comply with the guidelines suggested by the World Health Organization increasing the likelihood of a suicide contagion effect (Arafat et al. 2020; Sinyor et al. 2018; Young et al. 2017). Furthermore, specific content of what was being read was not analyzed, so it unknown if what they were reading spread misinformation, support suicide-myths, or be prosuicide in nature. It is not recommended that boys stop reading based on these findings – instead it is recommended that future research focus on the reasons and context behind why reading certain types of content might be related to suicide risk. It is also recommended that individuals turn to credible news and reading materials for sources of information.

Second, using education apps was also associated with increased suicide risk, specifically when boys also used social media in negative ways (such as high social comparison). Again, educational attainment tends to be a protective factor for suicide (Phillips and Hempstead 2017), so it was predicted that more time spent on educational apps

would be related to less suicide risk. However, the results revealed the converse. This link likely represents some underlying issue related to mental health, such as high levels of perfectionism or anxiety (Smith et al. 2018), where boys may be obsessively checking education type apps or feeling increased stress over school assignments. Boys are also less likely to seek out help in education and may feel more alone if stressed (Wimer and Levant 2011). The moderation with negative social media use may represent someone who passively scrolls social media (Escobar-Viera et al. 2018) while making a number of upward social comparisons (Nesi and Prinstein 2015), both of which have been related to mental health issues. It may be that some boys highly compare themselves to others in an online educational context and feel they do not measure up, increasing the likelihood of suicide risk. Notably, the use of educational apps was fairly low in comparison to other apps, so it is hoped that future research replicates this finding before any strong recommendations are made here.

Limitations

There are a few notable limitations to the current study. Participants were a community and not a clinical sample. Indeed, though the sample was moderate in terms of suicide risk, it is possible that participants may have completed suicide and the authors were unaware (since they may not have been in later waves of the study). To combat this, research assistants did a search for all participants who did not complete the final wave of the study, where suicide data was collected. The search was completed by using contact information (participant, parent, and a family member not living in the same household), obituaries, and social media. Research assistants were able to find information for approximately 60% of those who did not complete Wave 11. All were living except for one participant, and cause of death could not be determined. Thus, actual completed suicide rates were very low or non-existent, which was not surprising, given the overall rate of suicide and the sample size in the current study. Thus, suicide risk and not completion rates could be predicted in the study.

Second, the longitudinal data was self-reported, which is subject to reporter bias. This limitation was partially overcome by including the passive sensing data in Wave 11—however, the longitudinal results should be viewed with some caution. Passive sensing apps did not exist when data collection began in 2009 - future longitudinal research can utilize this technology to provide a more complete picture. There was also not a measure of suicide risk at the initial wave, so this could not be controlled longitudinally. Depression was included at this wave, so mental health struggles could be controlled for in the model, however, this is not a perfect correlation. Finally, there was an error with the media time measure (where two hours appears as a lower and upper limit). Thus, those participants who used media for exactly two hours a day may have put either category. This may have had a small impact on the results.

Conclusion

The current literature on suicide and media is extremely limited and plagued by methodological issues, such as cross-sectional and self-report designs. To combat these issues, the current study utilized a 10-year longitudinal study with passive sensing data at the final wave to examine associations between media use and suicide risk. Collectively, the results suggest that screen time may be related to suicide risk, both in the long- and the short-term. However, the results are nuanced, and certain patterns of media use tend to be riskier over time. Overall, time spent using various types of media was far more predictive of suicide risk for girls than it was for boys. This included high early and increasing trajectories of time spent on social media, television, and video games over a 10-year period. Thus, a more moderate approach to screen time that remains somewhat stable over time may be more developmentally appropriate for girls and could be integrated into media literacy programs. These findings were somewhat confirmed in the short-term (entertainment apps) using passive sensing apps. Additionally, being bullied combined with playing video games (for boys) appears to be particularly indicative of suicide risk. However, there were also several counter-intuitive findings for boys (including reading and education apps being risky for suicide). There is considerable debate in the research literature on the link between mental health in general, and suicide specifically. The results suggest that there is some cause for concern, but the picture is far more complicated than news headlines suggest.

Authors' Contributions SC conceived of the study, participated in its design and coordination and drafted the manuscript; JH conducted the statistical analyses, managed data collection and drafted the results section; WJD participated in the design and interpretation of the results and drafted part of the manuscript; QH drafted parts of the introduction and discussion and helped interpret the results; ES drafted parts of the introduction; SB managed the data collection and the passive sensing portion of the study; GJ drafted parts of the introduction. All authors approved the final version of the manuscript.

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Data Sharing and Declaration The datasets generated and/or analyzed during the current study are not publicly available but are available from the corresponding author on reasonable request.

Compliance with Ethical Standards

Conflict of Interest The authors declare that they have no conflict of interest.

Pre-registration This project was pre-registered with the Open Science Framework (see osf.io/6j8pw). Study design and description and basic hypotheses were included.

Research involving Human Participants This research was approved by the primary author's Institutional Review Board (IRB) and all participants were treated in compliance with the guidelines set forth by the American Psychological Association.

Informed Consent Informed consent was obtained at every wave of the study and participants could decline to participate at any stage.

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Systematic Review

Time Spent on Social Media and Risk of Depression in Adolescents: A Dose–Response Meta-Analysis

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Abstract: Adolescent depression is a worldwide public health concern and has contributed to significant socioeconomic burden. Investigating the association between time spent on social media (TSSM) and depression may provide guidance toward the prevention and intervention of adolescent depression. However, related literature reported mixed findings in terms of the relationship between TSSM and depression in adolescents. Hence, we conducted a comprehensive dose–response meta-analysis to clarify this issue. We conducted a systematic title/abstract and topic search of the relative terms in Web of Science, PubMed, PsycINFO databases through 9 January 2022. Odd ratios (ORs) were used to examine the pooled effect size of the association between TSSM and risk of depression. Dose–response analysis was evaluated by a generalized least squares trend estimation. Twenty-one cross-sectional studies and five longitudinal studies including a total of 55,340 participants were included. Overall, more TSSM was significantly associated with a higher risk of depression symptoms (OR = 1.60, 95%CI: 1.45 to 1.75) with high heterogeneity ($Q_{(29)} = 105.9$, $p < 0.001$; $I^2 = 72.6\%$). The association was stronger for adolescent girls (OR = 1.72, 95%CI: 1.41 to 2.09) than boys (OR = 1.20, 95%CI: 1.05 to 1.37). Five studies with seven reports were included in dose–response analysis. There was a linear dose–response association of TSSM and risk of depression. The risk of depression increased by 13% (OR = 1.13, 95%CI: 1.09 to 1.17, $p < 0.001$) for each hour increase in social media use in adolescents. TSSM is associated with depression in a linear dose–response and gender-specific manner, which suggests the need for better monitoring of adolescent social media use. However, motivation, content, and engagement on and exposure to social media use may also be important contributing factors, making it necessary to interpret the current findings with caution. Therefore, further research is required to clarify not only the causal link between TSSM and depression by randomized control studies but also the influence of other factors, such as active vs. passive social media use or different types of engagement or environments in which social media is used.

Keywords: social media use; depression; adolescents; meta-analysis; dose–response

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1. Introduction

Social media, also known as social networking, are internet-based interactive platforms where individuals and communities share and communicate [1,2]. In society today, children and adolescents grow up having both in-person and virtual social connections through social media (e.g., Facebook, Instagram, and WeChat) [3]. This continually emerging

internet-based social communication has greatly expanded adolescents' ability to make friends worldwide and makes it possible to connect with others anytime and anywhere. However, there is an ongoing debate about whether social media use is harmful to mental health or not [4,5], with some prior findings highlighting the psychological risk, especially depression, associated with excessive time spent on social medial (TSSM) in adolescence [6], while other studies report that there are only circumstantial correlations between TSSM and psychological problems [7]. Therefore, whether TSSM is associated with adolescents' mental health concerns is still unclear. Notably, an increase in depression has emerged in adolescence, particularly in adolescent girls, over the past ten years [4]. Social media use has also been increasing rapidly at the same time [3,6]. Thus, it is necessary to obtain insight into the association between TSSM and depression in adolescents.

Several theories may explain the inconsistent findings regarding TSSM and depression in adolescents. Based on both the uses and gratifications theory [8] and self-determination theory [9], adolescents may gain a sense of belonging [10,11] and increased self-esteem [12,13] through social media, which is then associated with lower levels of depression. In support of these theories, the association of TSSM and depression in adolescents would follow a U-shaped curve as a previous work suggested [14]. One study determined that the lowest risk of depression in adolescence was found when individuals use approximately 1 h of screen time per day compared with the no screen time group. Some work has also demonstrated the benefits of social media use on depression risk, while other studies have reported very small or null correlations between the two [7,15–18]. Currently, there are more studies reporting a significant positive association between TSSM and depression in adolescents [6,19–22], with a recent study supported a J-shaped curve between TSSM and depression [5]. The displacement hypothesis [23] may help to explain the dark side of excessive TSSM on depression. According to this hypothesis, TSSM may replace time for productive and/or active activities, such as physical activity or face-to-face interpersonal communication, thereby influencing adolescents' overall mental health, including depressive symptoms. Meanwhile, the strain theory may also explain the link between excessive TSSM and higher depression. Strains are usually caused by negative life events [24]. In a heavy involvement in TSSM, adolescents may experience more value strain, aspiration strain, and deprivation strain. All those strains are more likely to lead to depression [25]. Undoubtedly, another way to account for the high correlation between the two variables is to say that depressed adolescents may be more likely to indulge in social media to kill time [26] because depressed individuals have a negative cognitive bias, which may impair adolescents' self-regulation and result in excessive social media use. Finally, these contradictory findings regarding social media use and adolescent depression may also be related to the different methodologies that these studies used, such as the use of different populations and measurements.

Another noteworthy variable is gender. Most studies reported mixed-gender results about social media use and depression. Recently, researchers found that associations between TSSM and depression are different in boys and girls, with TSSM only associated with depression for girls [19,27]. This is in line with research demonstrating that girls use much more social media and place more importance on the closeness of their interpersonal relationships than boys [5], which may then lead to more relational aggression, fear of missing out on social media, and depression [28,29]. It should be noted that one study did find that boys' TSSM was also associated with depression; however, there was a stronger correlation for girls [6]. It is important to note that the relationship between TSSM and depression across gender is far more complicated than is outlined above. Numerous other factors may also affect these associations, such as active or passive use of social media [30], motivations for use [31], or environments to which adolescents are exposed [32].

To clarify the association between social media use and risk of depression in adolescents, several reviews have qualitatively summarized this association in children and adolescents [3,30,33,34]; however, these reviews often lack quantitative assessments. Relatedly, in these reviews, social media use is often measured more broadly, including other

information, such as frequency, purpose, and investment or addiction of social media use, instead of specifically TSSM. One prior meta-analysis [35] pooled the correlation of social media use (not specifically time-based) and depression in adolescents from 11 studies and found a small but statistically significant positive correlation with high heterogeneity. In another meta-analysis, social media use was measured using both TSSM and frequency of social media use, and similar findings were reported [36]. However, responses regarding frequency of social media use were most commonly measured on a scale from "never" to "almost every day", which have little variability because most adolescents use social media every day [5]. Similarly, neither meta-analysis explored sources of heterogeneity, and there was no pooled estimation of the relation between TSSM and risk of depression for adolescents, which may be important for providing evidence-based guidelines regarding TSSM. Thus far, there has been no meta-analysis that has examined a dose–response association between TSSM and risk of depression. In sum, it is clear that a more comprehensive meta-analysis is needed to quantify the dose–response association between TSSM and the risk of depression in adolescents.

The purpose of the current study is to summarize evidence related to the association between TSSM and depression in adolescents by pooling the risk of depression with TSSM for adolescents, quantifying a dose–response association, and exploring the heterogeneity of the included studies. Based on displacement theory, we hypothesize that more TSSM will be associated with a higher risk of depression in adolescents, with a linear dose–response association. Moderation by gender will also be included as an exploratory hypothesis. However, because of its non-experimental nature, no causal inferences can be drawn in the current study.

2. Methods

2.1. Search Strategy

This study was conducted according to the PRISMA guidelines [37] (see Table S1). Electronic databases, including Web of Science, PubMed, and PsycINFO, were searched systematically using title/abstract, and topic (through 9 January 2022) with no publication type or language restriction. To determine "social media" related search terms, a stratified searching strategy was adopted. Firstly, we searched the PubMed database using the most general terms of social media, such as "social media", "digital media", "social networking", "SNS", and "screen media". Next, we screened all study titles and hundreds of abstracts, ending up with 56 different terms. Based on using frequency and generality, we divided them into two categories: general social media-related terms and specific social media-related terms. All general social media terms were included in the final search. However, some rarely used specific social media-related terms, such as "Digg", and "Edmodo", were deleted. Finally, three sets of medical subject terms (MeSH) and their combinations were used in the search, including "social media", "social network*", "SNS", "digital media", "screen media", "online media", "internet media", "collaborative filtering site*", "media sharing site*", "Mashups", "Facebook", "Twitter", "Instagram", "YouTube", "Snapchat", "LinkedIn", "WhatsApp", "Pinterest", "Blog", "Wiki", "Tumblr", "Myspace", "Google+", "Reddit", "WeChat", "QQ", "WordPress", "Telegram", "Flickr", "Skype", "Vine", "Tweeting", "podcasts", "Tik Tok", "Sermo", "Google Groups", "Forum and Blog", "Second Life"; "depress*"; "adolescen*", "juvenile*", "teenager*", "high school student*", "middle school student*", "children". The asterisk indicates that the search was inclusive of larger words that contained the word or word fragment. Additionally, references of retrieved articles were screened.

2.2. Inclusion and Exclusion Criteria

Studies were included if the following criteria were fulfilled: they were an observational study; they reported complete correlation indices of TSSM with depression which could be subsequently converted into an odds ratio (OR) with 95%CI; and average participant age was between 10 and 19 years old. Articles not meeting the inclusion criteria were

excluded. Studies were also excluded if they reported mixed screen time, such as time spent playing internet games or watching online videos, as this would cause the measure of TSSM to be unclear. Authors were contacted if data were missing. Only one study was included if multiple articles reported the same research. The screening of titles/abstracts and topic and subsequent full-text assessment were performed independently by two authors (J.X. and P.X.). When the two authors made different decisions, they discussed the full text and determine its eligibility for inclusion together. If the two authors still disagreed, a third author (M.L.) helped to resolve the disagreement. Figure 1 displays the screening process.

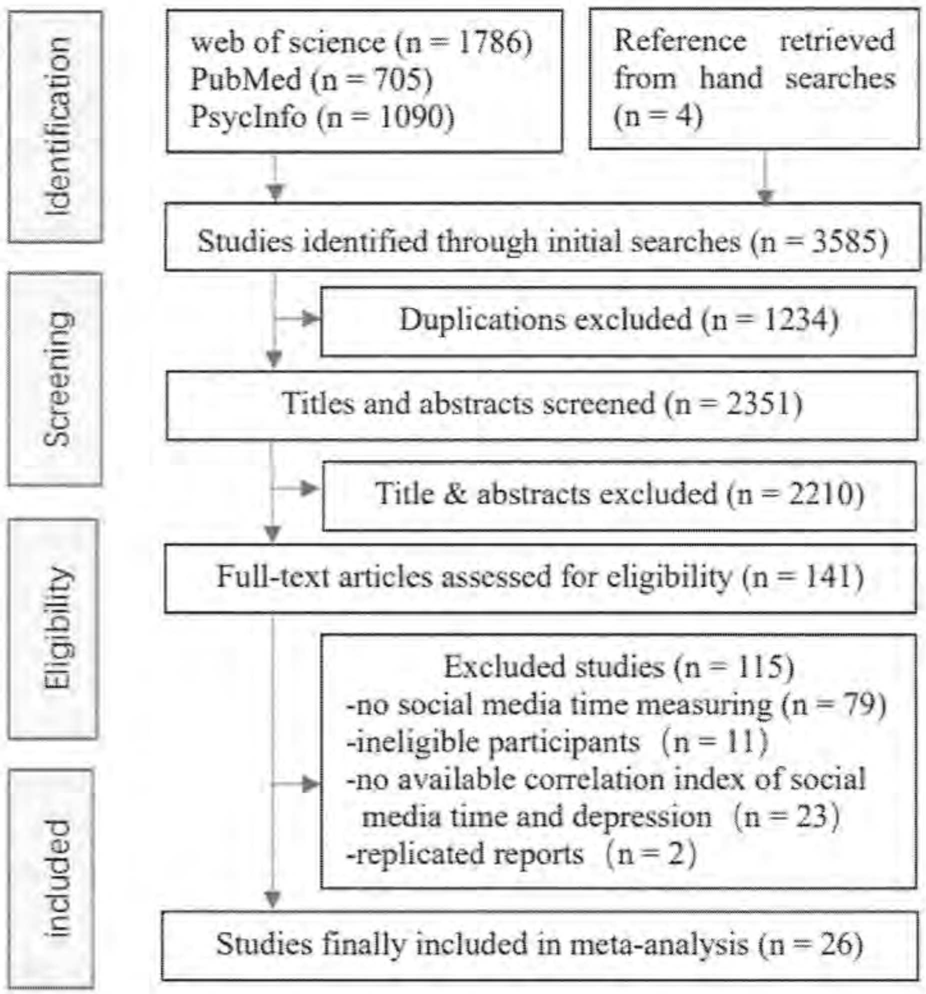

Figure 1. Flow chart of article screening process.

2.3. Data Extraction

All related data (i.e., the first author's name, published year, country, study objective, study design, participants' gender and age, sample size, number of cases (for dose–response analyses), the detailed measure of TSSM and depression, and the correlation index of TSSM with depression) of eligible studies were extracted using EpiData V.3.1 and Excel by two investigators. For the quality assessment, we referenced the Meta-analysis of Observational Studies in Epidemiology (MOOSE) [38] and the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) [39] guidelines. Study quality was rated on a scale with a maximum of 8 points based on the following criteria: appropriate selection of participants (1 point); proper measures of TSSM (2 points) and depression (2 points);

appropriate methods to deal with the design issues (1 point); appropriate handling of confounds (1 point) and proper statistical methods (1 point).

2.4. Statistical Analyses

Pooled data were expressed as ORs with 95%CIs. Studies that provided effect sizes stratified by gender were treated as two separate reports. For the studies reporting correlation coefficients, we converted the correlation coefficients to ORs with 95%CIs [40]. For one study using 1–3 h/day as the reference category for TSSM, we recalculated the ORs and 95%CIs using the no TSSM group as the reference category [40]. For studies that provided multiple categories' effect sizes, we combined the corresponding estimates using the Excel RRs proposed by Hamling et al. [41]. The Q statistic was used to evaluate the heterogeneity among studies, and it was quantified by I^2. Low, moderate, and high heterogeneity were indicated by the 25%, 50%, and 75% values of I^2, respectively. If $I^2 < 50\%$, a fixed-effects model was used to estimate the pooled OR and corresponding 95%CI; otherwise, a random-effects model was administrated. To assess the sources of heterogeneity, we performed several subgroup analyses including gender, geographical regions, the measure of TSSM and depression, and sample size. In addition, sensitivity analyses were conducted to test the robustness of the results. Furthermore, tunnel plot asymmetry was used to detect publication bias of the included studies in this meta-analysis, and then Begg's and Egger's tests were performed to measure the publication bias.

A specific dose–response analysis was conducted to further estimate the association between TSSM and risk of depression. For the studies that did not report the median or mean of each category, the dose was calculated as the midpoint of the lower and upper boundaries in each group; for the open-ended lower or upper group, the boundary was assumed as the same as the closest group. Both non-linear and linear associations between TSSM and depression were tested. The potential non-linear dose–response relationship between TSSM and depression was estimated using a restricted cubic spline model with three knots of the TSSM distribution. Significance was then tested by setting the second spline coefficient equal to zero. A random-effects model was conducted to examine the trend because of the high heterogeneity among the studies. The dose–response coefficients and corresponding 95%CIs were calculated using a generalized least squares regression. The significance level was set at $p < 0.05$. All statistical analyses of this study were performed with STATA V12 software (Stata Corp, College Station, TX, USA).

3. Results

3.1. Characteristics of the Included Studies

According to the inclusion and exclusion criteria, 30 reports from a total of 26 studies, including a total of 55,340 participants, were included in the final analyses (see Figure 1). The characteristics of the included studies are summarized in Table 1. Twenty-one studies [6,15–22,27,42–51] were cross-sectional, and five were longitudinal [52–56]. Of note, one longitudinal study conducted by Coyne et al. [27] was actually a cross-sectional design for the relationship between TSSM and depression because they reported eight cross-sectional correlations based on data collected from each wave in eight years (2009 to 2017). We incorporated the seventh wave data, which was conducted in the most recent year and which also met the age criteria (19 years). For another four-wave longitudinal study [56], the authors reported a general between-persons and a within-persons regression association with means and standard deviations in the first wave and the last wave. We converted the data into ORs with 95%CIs using the general between-persons correlation for the four waves, with means and standard deviations in the last wave. Across all studies, sample size varied widely from 85 to 11,423 participants. Five studies [6,19,27,49,51] analyzed gender groups separately. However, we combined the total effect size for one study [51] that reported gender-specific results because the sample sizes of the single genders were too small. The mean age of all participants ranged from 11 to 19 years. Three studies reported the age range of the participants with no exact mean ages provided [21,42,47].

Eleven studies were conducted in Europe [6,16,18,19,21,43,47,49,52,53], nine in North America [27,31,42,44,46,48,50,51,56], four in Asia [15,17,45,55], one in Brazil [20], and one in Australia [22]. For the measure of TSSM, most of the studies (22 of 26) used total TSSM while the other four studies [31,43,46,53] used time spent on specific social media platforms, such as Facebook or Instagram. Meanwhile, several questionnaires, including the Center for Epidemiological Studies-Depression scale [57] (CESD, 11 studies), the Short version of the Mood and Feelings Questionnaire (SMFQ, 7 studies) [58], the Beck Depression Inventory [59] (BDI, 2 studies), the Patient Health Questionnaire-9 [60] (PHQ9, 3 studies), the Children's Depression Inventory [61] (CDI, 1 study), the Brief Symptom Inventory [62] (BSI, 3 studies), the Hospital Anxiety and Depression Scale [63] (HADS, 1 study), the scale of the Original Symptom Checklist-Depression dimension [64] (OSCD, 1study), and one question asking "how often you felt depressed" [54] were used to measure depressive symptoms across all included studies. The quality score of all included studies ranged from 3 to 7, with 19 studies obtaining a score of greater than 5 (see Table S2).

3.2. Associations between TSSM and Depression Risk

The overall pooled OR was 1.59 (95%CI: 1.44 to 1.77; $p < 0.001$) with high heterogeneity ($Q_{(27)} = 105.9$, $p < 0.001$; $I^2 = 72.6\%$). The combined OR was 1.61 (95%CI: 1.44 to 1.81) with high heterogeneity ($Q_{(24)} = 97.25$, $I^2 = 75.3\%$) for cross-sectional studies and 1.57 (95%CI: 1.44 to 1.71) with almost zero heterogeneity ($Q_{(4)} = 3.46$, $I^2 = 0\%$) for longitudinal studies (see Figure 2).

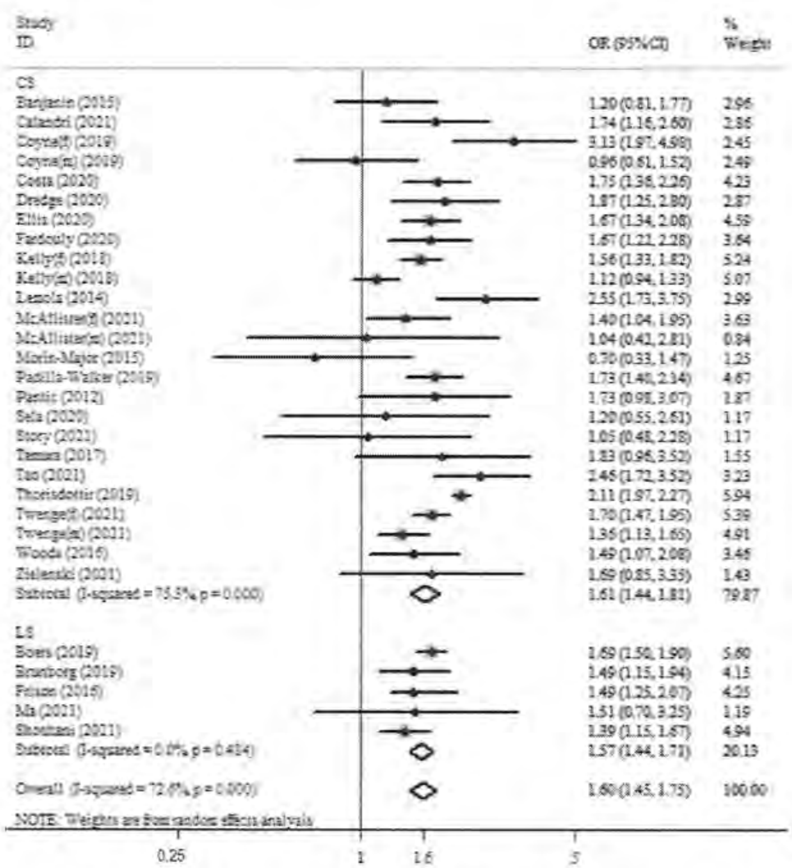

Figure 2. Forest plot of the association between time spent on social media (hours/day) and risk of depression in adolescents by study design. OR of depression for higher daily time using social media compared with reference groups and corresponding 95%CI. CS, cross-sectional; LS, longitudinal; f, female; m, male.

Table 1. The Characteristics of the included studies.

Study	Design	Main Study Objective	Country; Sample Size (Female)	Age (Years)	Measure of Time Spent on Social Media	Depression Measure
Banjanin et al. 2015	CS	Investigated the potential relationship between internet addiction and depression in adolescents.	Serbia; 336 (66%)	18	Self-report daily time spent on social networking; Response: self-administered open answer	CESD
Boers et al. 2019	LS	Repeatedly measured the association between screen time and depression.	Canada; 3826 (47%)	12.7–15.7 Grade 7–11	Self-report how much time per day they spend on social networking sites; Response: 0–30 min, 30 min–1.5 h, 1.5 h–2.5 h, ≥3.5 h	BSI
Brunborg et al. 2019	LS	Examined association between time spent on social media and depression, conduct problems, and drinking.	Norway; 763 (55%)	15.22	Self-report daily hours spent on social media; Response: <1 to >15 in hourly increments	PHQ9
Calandri et al. 2021	LS	Investigated the relationships between social media use and depressive symptoms.	Italy; 336 (48%)	13.0 (13–15)	Self-report daily hrs spent on communicating online with friends through social networks; Response: 0, 1, 2, ≥3	CESD
Costa et al. 2020	CS	Examined the associations between self-reported and accelerometer-measured movement behaviors and depressive symptoms.	Brazil; 610 (52%)	16.30 (14–18)	Self-report daily hours spent on social media; Response: <2, 2–4, ≥4	CESD
Coyne et al. 2019	CS	Examined the association between time spent using social media and depression and anxiety at the intra-individual level.	USA; 500 (52%)	13–20	Self-report daily hours on social media; Response: 1 (0) to 9 (>8)	CESD
Dredge et al. 2020	CS	Examined the association between online gaming and social media use frequency, depression, and other mental health.	China; 320 (47%)	13.98 (12–17)	Self-report daily time spent on social media; Response: 1 (0) to 9 (>8)	PHQ9
Ellis et al. 2020	CS	Examined the relationships between psychological adjustment and stress and the initial COVID-19 crisis.	Canada; 1054 (76%)	16.68 (14–18)	Self-report daily time spent using social media platforms; Response: <10 min, 10–30 min, 31–60 min, 1–2 h, 2–3 h, 3–5 h, 5–10 h, to more than 10 h	BSI
Fardouly et al. 2020	CS	Investigated differences between preadolescent users and non-users of various social media platforms on mental health.	Australia; 528 (269)	11.19	Self-report daily time spent on social media platform; Response: 0 (0), 1 (<5 min), 2 (5–15 min), 3 (15–30) min, 4 (30 min–1 h), 5 (1–2 h), 6 (2–4 h), 7 (4–6 h), 8 (6–8 h), 9 (8–10 h), 10 (10–12 h or more).	SMFQ
Frison et al. 2016	LS	Examined the relationships between peer victimization on Facebook, depressive symptoms, and life satisfaction.	Belgium; 1621 (51%)	14.76 (12–19)	Self-report daily hours spent on Facebook; Response: 0 (0), 1 (0.5), 2 (0.5–1), 3 (1–1.5), 4 (1.5–2), 5 (2–2.5), 6 (2.5–3), 7 (3–4), 8 (4–5), 9 (>5), 10 (always logged in and available for interaction)	CESD

Table 1. *Cont.*

Study	Design	Main Study Objective	Country; Sample Size (Female)	Age (Years)	Measure of Time Spent on Social Media	Depression Measure
Kelly et al. 2018	CS	Assessed association between social media use and adolescents' depressive symptoms.	UK; 10,904 (50%)	14.30	Self-report daily hours spent on social media; Response: 0, <1, 1–3, 3–5, ≥5	SMFQ
Lemola et al. 2014	CS	Sought a better understand the interplay between sleep, depressive symptoms, and electronic media use at night	Switzerland; 362 (45%)	14.82 (12–17)	Self-report daily duration spent online on Facebook; Response: self-administered open answer	CESD
Ma et al. 2021	LS	Examined how time spent on types of screen use was associated with depressive symptoms.	Sweden; 3556 (51%)	8 grades	Self-report daily hours spent on social media; Response: >2, 2, 1, <1, 0	Question of how often felt depressed
McAllister et al. 2021	CS	Compared associations across specific screen media activities and examined associations with self-harm behaviors.	UK; 4243 (55%)	13.75 (13–15)	Self-report time diary on one weekday and one weekend day from 4:00 am one day to 4:00 am the next day; for each 10 min time slot	SMFQ
Morin-Major et al. 2015	CS	Explored the associations between Facebook and basal levels of cortisol among adolescents.	Canada; 94 (53%)	14.50 (12–17)	Self-report weekly time spent on Facebook; Response (hours): 1 (<1), 2 (2–5), 3 (6–10), 4 (11–15), 5 (16–20), 6 (>21)	CDI
Padilla-Walker et al. 2019	CS	Explored the links between parental media monitoring and adolescents' internalizing symptoms.	USA; 1155 (51%)	10–20	Self-report daily time spent on social media; Response: 1 (none), 2 (less than 30 min), 3 (31–60 min), 4 (1–2 h), 5 (2–3 h), 6 (3–4 h), 7 (5–6 h), 8 (7–8 h), and 9 (≥9 h)	CESD
Pantic et al. 2012	CS	Investigated the relationship between social networking and depression in adolescent.	Serbia; 160 (68%)	18.02	Self-report daily time spent on social networking sites; Response: self-administered open answer	BDI
Sela et al. 2020	CS	Tested the association between family environment and excessive internet use among adolescents.	Israel; 85 (41%)	14.04 (12–16)	Objectively measure time logged in various social medias on the smartphone for 14 days; Response: average time per day spent on social media.	BDI
Shoshani et al. 2021	LS	Examined the influence of the COVID-19 pandemic on children and adolescents' mental health and well-being, and potential risk and protective moderators.	Israel; 1537 (52%)	13.97	Self-report daily hours spent on social media; Response: 0, <1, 1, 2, 3, 4, 5, 6, ≥7.	BSI
Story 2021	CS	Assessed the link between the time spent on social networking sites and depression among 9th and 10th grade high school students.	USA; 85 (56.5%)	14.88 (14–16)	Self-report the number of times and the number of min they spent on SNS daily. Response: sum of the min was divided by the sum of the times	PHQ

Table 1. *Cont.*

Study	Design	Main Study Objective	Country; Sample Size (Female)	Age (Years)	Measure of Time Spent on Social Media	Depression Measure
Tamura et al. 2017	CS	Investigated the relationship between mobile phone use and insomnia and depression in adolescents.	Japan; 295 (41%)	16.20 (15–19)	Self-report daily time spent on social networking sites; Response (min): 0, <30, 30–60, 60–120, ≥120	CESD
Tao et al. 2021	CS	Assessed the relationships among social media use, individual and vicarious social media discrimination, and mental health.	USA; 407 (82%)	16.47 (15–18)	Self-report Total time spent on social media per week; Response: multiple days/week by h/day	CESD
Thorisdottir et al. 2019	CS	Documented the prevalence of social media use and investigate the relationship of both active and passive social media use to anxiety and depressed mood.	Iceland; 10,563 (50%)	14–16	Self-report daily hours on social media; Response: 1 (0) to 8 (≥6)	OSCD
Twenge et al. 2021	CS	Examined associations between different types of screen activities and mental health.	UK; 11,423 (50%)	13.77 (13–15)	Self-report hours spent on social networking or messaging sites on a normal weekday during term time; Response: <0.5, 0.5–0.99, 1–1.99, 2–2.99, 3–4.99, 5–6.99, ≥7	SMFQ
Woods et al. 2016	CS	Examined how social media use related to sleep quality, self-esteem, anxiety and depression.	UK; 467	11–17	Self-report daily hours spent on social media; Response: 1 (<1) to 6 (>6)	HADS
Zielenski et al. 2021	CS	Examined the relationship between Instagram use, social comparison, and depressive symptoms.	USA; 110 (56%)	12–18	Self-report daily hours spent on Instagram; Response:<1 h; 1–2 h; 2–3 h; 3–4 h; 4–5 h; >5 h	CESD

Note: CS, cross-sectional study; LS, longitudinal study; CESD, the Center for Epidemiological Studies-Depression scale; SMFQ, the short version of the Mood and Feelings Questionnaire; BDI, the Beck Depression Inventory; PHQ9, the Patient Health Questionnaire-9; CDI, the Children's Depression Inventory; BSI, the Brief Symptom Inventory; HADS, the Hospital Anxiety and Depression Scale; OSCD, the scale of the Original Symptom Checklist-Depression dimension.

3.3. Subgroup and Sensitivity Analyses

Subgroup analyses show that the association between TSSM and risk of depression was moderated by gender and the measure of depressive symptoms (see Table 2).

Table 2. Moderation analyses for time spent on social media–depression risk association.

Variables	K	OR	95%CI	Z	Heterogeneity Test		
					I^2(%)	Q_w	*p*-Value
Gender, $Q_{b(2)} = 40.44$ ***							
Boys	4	1.20	1.05–1.37	2.62 *	8.9	3.29	0.349
Girls	4	1.72	1.41–2.09	5.38 ***	66.8	9.03	0.029
Mixed	22	1.67	1.52–1.84	10.27 ***	60.8	53.14	0.001
Age, $Q_{b(2)} = 9.28$ **							
<14	10	1.54	1.34–1.79	5.85 ***	54.9	19.96	0.018
>14	17	1.61	1.41–1.84	7.10 ***	79	76.11	<0.001
Mixed	3	1.66	1.40–1.97	5.73 ***	0	0.55	0.758
Regions, $Q_{b(3)} = 4.13$							
Europe	14	1.54	1.33–1.79	5.74 ***	82.8	75.58	<0.001
North America	10	1.68	1.41–1.99	5.88 ***	62.1	23.73	0.005
Asia	4	1.47	1.25–1.73	5.38 ***	0	2.41	0.491
Others	2	1.72	1.41–2.09	4.73 ***	0	0.05	0.820
Measure of Time Spent on Social Media, $Q_{b(1)} = 0.23$							
Total	26	1.	1.45–1.76	9.39 ***	73.7	95.11	<0.001
Specific	4	1.56	1.01–2.40	1.99	71.6	10.56	0.014
Measure of Depression, $Q_{b(5)} = 56.7$ ***							
SMFQ	7	1.44	1.26–1.65	5.20 ***	62.3	15.92	0.014
CESD	11	1.77	1.48–2.10	6.39 ***	60	24.98	0.005
BDI	2	1.52	0.96–2.41	1.79	0	0.55	0.458
PHQ9	3	1.55	1.25–1.91	4.04 **	0	1.88	0.391
BSI	3	1.59	1.41–1.80	7.50 ***	36.2	3.14	0.208
Others	4	1.51	1.02–2.24	2.04 *	76.4	12.73	0.005
Sample Sizes, $Q_{b(1)} = 0.35$							
>1000	13	1.55	1.37–1.76	6.88 ***	83.3	33.5	0.006
<1000	17	1.65	1.42–1.92	6.54 ***	52.3	72.050	<0.001

Note: SMFQ, short version of the Mood and Feelings Questionnaire; CESD, the Center for Epidemiological Studies-Depression scale; BDI, the Beck Depression Inventory, PHQ9, the Patient Health Questionnaire-9; BSI, Brief Symptom Inventory; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

For sensitivity analyses, no single study influenced the result significantly when studies were individually omitted (see Figure S1). There was also no significant change in the results when studies where another effect size was converted to an OR were excluded from analysis (the pooled OR was 1.47, 95%CI: 1.29 to 1.67, $p < 0.001$; $I^2 = 54.4\%$).

3.4. Publication Bias

Begg's test did not show significant publication bias ($p = 0.986$) (see Figure 3), and Egger's linear regression test suggested a mildly significant publication bias ($p = 0.039$). However, no trimming was needed to be performed when the nonparametric trim-and-fill method was used, demonstrating the reliability of the findings (see Figure S2).

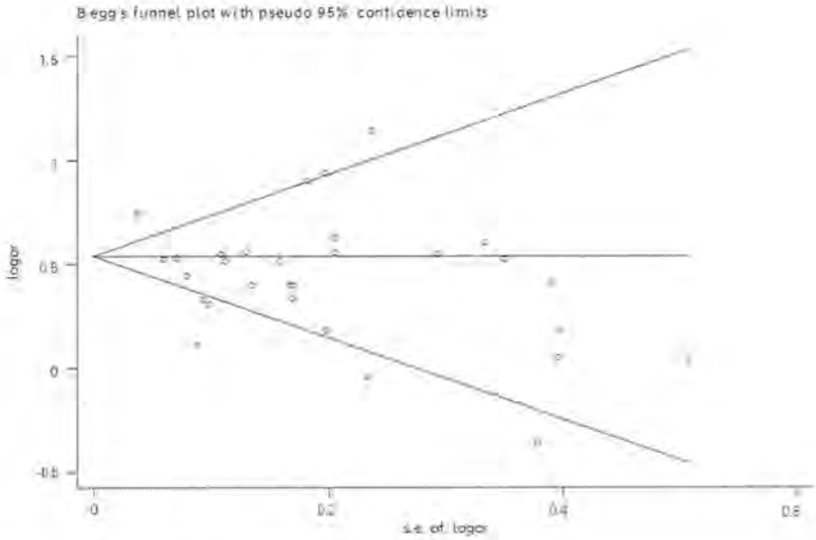

Figure 3. Funnel plot of publication bias.

3.5. Dose–Response Association between TSSM and Risk of Depression

Five studies [6,17,19,20,54] (seven reports) were included for the dose–response analysis. The results showed a total linear association between TSSM and risk of depression ($p = 0.888$ for non-linearity, $p < 0.001$ for linearity; see Figure 4) with high heterogeneity between studies ($Q = 70.33$, $p < 0.001$). The risk of depression increased by 13% (OR = 1.13, 95%CI: 1.09 to 1.17, $p < 0.001$) for each hour increase in social media use in adolescents. For samples in which gender was examined separately, there were linear associations between TSSM and depression for both girls and boys ($p = 0.720$ for non-linearity). Specifically, the risk of depression increased by 13% (OR = 1.13, 95%CI: 1.08 to 1.16, $p < 0.001$) for girls and by 9% (OR = 1.09, 95%CI: 1.03 to 1.15, $p = 0.002$) for boys for each hour increase in social media use in adolescents.

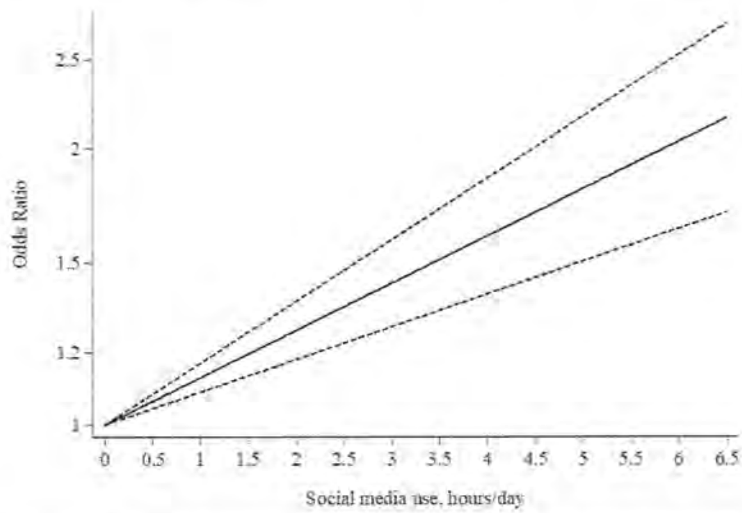

Figure 4. The generalized least squares trend estimated dose–response of time spent on social media and risk of depression in adolescents. Time of social media use was modelled with a restricted cubic spline in a two-stage random-effects dose–response model. The ORs are plotted on the log scale. Dashed lines represent the 95%CIs for the spline model. No social media use served as the referent category.

4. Discussion

The present comprehensive meta-analysis investigated the association between TSSM and the risk of depression in adolescents. Our findings reveal that adolescents with higher daily TSSM had a 59.6% increase in terms of the risk of depression when compared with the reference group. Furthermore, the risk of depression increased by 13% for each hour increase in social media use, and these associations were stronger for adolescent girls than boys; however, boys still demonstrated a significant increase in depression risk. The findings are consistent with the WHO guidelines, which recommend limiting daily screen time for adolescents [65] and which are in agreement with the detrimental effect of high levels of social media use for adolescents suggested by some previous studies [4,5]. Moreover, the linear dose–response analysis of the current study demonstrated that with an increase in hours spent on social media each day, the risk of adolescent depression increased linearly. Therefore, it can be inferred that excessive TSSM may be a strong risk factor for adolescents' depression. Consistently, Twenge et al. [6] suggested that excessive TSSM (>5 h) was associated with a more than 2-fold risk of depression (OR = 2.31, 95%CI: 1.98 to 2.70 for girls; OR = 2.05, 95%CI: 1.59 to 2.64 for boys), after controlling for relevant covariates such as age, family income, ethnicity, and presence of biological father; a similar risk of depression was found in the highest TSSM group (after recalculating using the 0 h/day category as the reference category) in girls (>5 h) in the study conducted by Kelly et al. [19]. Of note, although the included studies in the current meta-analysis have controlled for most relevant covariates (e.g., age, gender, family income, etc.), some other covariates (e.g., physical activity, which was shown to be a protective factor for adolescent' depression) could also influence the results [66,67]. The current findings still need further support by future studies controlling all related covariates.

One notable finding of the current meta-analysis is the significant difference in the pooled estimate between boys and girls. Generally, a significant positive association between TSSM and risk of depression emerges in both girls and boys; however, this pattern is much larger for girls. This finding is consistent with previous studies regarding the association between adolescent social media use and risk of depression [6,68], but it is inconsistent with a longitudinal study examining media exposure (e.g., television, videocassettes, video games, and radio) and risk of depression [69]. In the aforementioned study, the authors found that a lower risk of depression was associated with more total media exposure for teenage girls. Social media use specifically, which was not assessed in this longitudinal study, could underlie these inconsistent results. Social media provides individuals multiple ways of seeking and maintaining social bonds [22,29,45]. Adolescents who fear of missing out social communication hope to continually stay connected with their peers and to stay updated on others' states [70]. Currently, adolescent girls spend much more time on social media than boys [5,6,19,20,32], which may be attributed to the tendency among girls to emphasize close, intimate friendships [28,71]. Therefore, girls are more likely to experience fear of missing out [72] or being harassed [19,20] on social media, which has been associated with risk of depression [28,29]. Thus, it is understandable that previous studies may not have detected gender differences when examining total screen time (including video/computer games, computer/internet use, and television) and risk of depression. Studies stratified by media or screen category and gender are needed to clarify this question. Higher TSSM was associated with a higher risk of depression in the current meta-analysis across both younger and older adolescence. This seems inconsistent with a previous review [14] in which a significant screen time–depression risk was detected only in younger adolescents (<14 years). One possible reason is that some studies included in the current meta-analysis had a range of both younger and older adolescents [20,27,42,45–47,53]. For example, the study conducted by Woods et al. included participants ranging in age from 11 to 17 years [47]. Some social media platforms have an age limit for creating social media pages (e.g., 13 years of age for Facebook), which may also influence the results. Many studies with no stratification by age precluded us from clarifying the issue yet highlight an important area of future study. The included studies in this meta-analysis also used

multiple different questionnaires measuring depressive symptoms. Interestingly, depression measurement type played a significant moderating role in the association between TSSM and risk of depression. Specifically, the two studies [15,16] in which depression was measured using the BDI demonstrated no significant correlation. The way in which this measure assessed depression may be an important factor to consider. In fact, previous work has asserted that the BDI is a good measure for identifying major depressive disorder [73]; thus, it may not be as accurate when examining a non-clinical population. Similarly, the sample sizes of the two studies were relatively small (n = 85/160), which may be non-comparable and may have caused a misleading correlation. Further studies with a larger sample size are needed to clarify differences in depressive symptoms related to specific measurement scales.

The current meta-analysis comprehensively quantified the dose–response association between TSSM and the risk of depression in adolescents. The large sample size allowed the meta-analysis of dose–response associations between TSSM, ranging from low to high duration, and risk of depression. This study also provided more precise results with smaller confidence intervals than in the previous original studies. International and national guidelines or strategies [74,75] promoting limited screen time for children and adolescents are supported by the current study. Although the implication of the study is not explicit because research is still evolving in this field, our findings reinforce TSSM limitations for adolescents in a gender-specific manner, particularly for girls, noting that the risk of depression increased linearly with an increase in daily hour of social media use. These results are important for adolescents and their parents or other caregivers because they clarify the potential risk of unlimited time on social media, and in turn, prompt them to take steps to promote positive adolescent health and development. Although research concerning links between TSSM and depression in adolescents has given rise to the development of media use policies, particularly regarding smart phone use, most school policies permit their students to use phones during non-instructional times in a school day, such as during recess and lunch [76]. Our findings provide more evidence for school policymakers, as well as national and international public health policymakers, for developing guidelines for appropriate social media use and consumption to reduce depressive risk for adolescents. On the other side, considering the effects of digital technology on the field [77], future study on digital technology innovations is also required for better assisting in "co-care" monitoring adolescents' media use.

There are also important limitations to this study, making it necessary to interpret the findings with caution. First, all included studies were observational, in which the results may be influenced by other potential covariates not yet considered. Hence, we cannot speak to causality in the interpretation of the results. Relatedly, adolescents who had higher depressive symptoms may have recall bias in which they tend to endorse excessive social media use more so than those who had fewer depressive symptoms. As a result, studies in which social media use is measured more objectively are needed in the future. Second, although the search strategies did not restrict language, English databases may lead to the omission of non-English articles as well as non-English terms around social media, which may have an important role in better understanding this association. Although we used a stratified search strategy, there are still various specific social media platforms and social media-related terms, especially those only used in specific countries or regions, that were not included. Third, distinct measurement scales of depressive symptoms and diagnostic criteria for depression could increase variability across included studies. More studies with consistent instruments and diagnostic criteria for depression are needed to support the current findings. Relatedly, understanding the differences in association within a clinical vs. non-clinical population may be important for better understanding for whom TSSM may have a more harmful effect. Most of the participants of eligible studies were collected from Europe and North America, which may limit the generalization of the current findings. Therefore, further investigations from other cultures, particularly focusing on developing countries/regions, are needed to replicate the current findings.

5. Conclusions

Our findings provide evidence that more TSSM is associated with a higher risk of depression in adolescence in a linear dose–response manner, especially for teenage girls. Therefore, prevention efforts targeting a better understanding of the effects of TSSM, particularly for adolescent girls, may be a key component to lessen the risk of depression as social media continues in its global popularity. However, other variables, such as motivation, different platforms, and exposure to social media use may influence this association, making it necessary to interpret the findings with caution. Future research using randomized control studies is required to clarify the causal link between TSSM and depression, as well as the different effects of how adolescents use social media and the environments in which they use it.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/ijerph19095164/s1. Table S1: The PRISMA checklist of this meta-analysis; Table S2: The risk of bias for included studies; Figure S1: The sensitivity analyses by omitting the included studies one by one; Figure S2: The metatrim analysis by nonparametric trim-and-fill method.

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The Impact of Snapchat Filters on Self-esteem and Social Identity among female Adults

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ABSTRACT

This research aims to investigate the influence of Snapchat filters on self-esteem and social identity among female adults, specifically targeting 11th-grade students in government schools in Delhi. In an era characterised by the prominence of social media platforms, especially Snapchat, the utilisation of filters that modify appearance has become widespread. The filters, intended to augment physical attributes, may generate a significant disparity between users' authentic and digitally altered appearances, which could influence their self-perception and sense of identity.

This qualitative study utilised semi-structured interviews with 17 female students from government schools to investigate their experiences and perceptions of Snapchat filters. The results indicate a notable influence on self-esteem and social identity. A significant 71% of participants indicated a reduction in self-esteem, experiencing feelings of inadequacy when juxtaposing their natural appearance with their filtered images. The study indicates that these filters play a role in altering social identity, with 82% of students reporting a sense of pressure to adhere to societal beauty standards propagated by the filters. The pressure to present an idealised version of oneself online has led to a preference for filtered appearances over natural looks, resulting in a distorted self-image.

The research highlights the psychological implications of utilising Snapchat filters, indicating that persistent exposure to augmented images may result in a dependence on external validation and a disjunction between online

identities and real-world selves. The findings indicate an increasing necessity for awareness and interventions focused on the effects of social media filters on the mental health of young adults. It is essential for educators and mental health professionals to formulate strategies aimed at fostering positive self-esteem and a healthy social identity, thereby assisting students in managing the challenges posed by digital beauty standards.

Keywords: Snapchat filters, Self-esteem, Social identity, Female adults, 11th-grade students, Government schools, Delhi

Introduction

The introduction functions as a crucial element of any research study, establishing the foundation for the entire project by explicitly defining the research topic, delineating the problem, and articulating the study's objectives and significance. The impact of social media on self-perception and identity has emerged as a significant focus of research in recent years, especially with the introduction of features by platforms such as Snapchat that enable users to modify their appearance through filters. These filters, often perceived as innocuous entertainment, can significantly influence users' self-esteem and social identity, particularly among young female adults who are concurrently facing the complexities of adolescence and identity development.

In the context of India, where social media usage is rapidly increasing, it is essential to investigate the impact of these digital tools on the psychological well-being of young adults. Government schools in Delhi cater to a diverse student population, many of whom originate from backgrounds where access to technology and social media is a relatively recent development. The influence of Snapchat filters on students' self-esteem and social identity warrants careful examination, as these tools may perpetuate unrealistic beauty standards and lead to feelings of inadequacy.

Snapchat filters are engineered to enhance or modify physical appearances, providing users with the capability to smooth skin, alter facial structures, and

incorporate playful elements such as animal ears or crowns. Although these alterations may appear insignificant, they can result in considerable psychological effects. A study conducted by the Dove Self-Esteem Project revealed that 80% of girls utilise filters or photo-editing applications by the age of 13, with 44% expressing feelings of "unattractiveness" in the absence of digital enhancement. The increasing reliance on filtered images may lead to a distorted self-image, as individuals might begin to perceive their unaltered appearance as insufficient. In India, the situation is exacerbated by cultural factors that prioritise fair skin and slender figures as the ideal beauty standards. When Snapchat filters predominantly reflect these ideals, they can intensify feelings of inadequacy among users who do not naturally conform to these standards. For female students in government schools in Delhi, who may already be encountering socio-economic challenges, the pressure to adhere to these digital beauty standards can be especially intense.

This research investigates the impact of Snapchat filters on the self-esteem and social identity of 11th-grade female students attending government schools in Delhi. This research employs a mixed-methods approach, incorporating surveys and focus group discussions, to capture the quantitative impact of filter usage on self-esteem as well as the qualitative experiences related to social identity formation in the digital age. The research will also examine the impact of peer influence, as social media interactions frequently represent communal experiences in which validation from peers may further strengthen the inclination to portray a digitally enhanced version of oneself. The results of this research are anticipated to carry substantial implications for educators and mental health practitioners. Investigating the influence of Snapchat filters on the self-esteem and social identity of young female adults may contribute to the formulation of interventions aimed at fostering a healthier self-image and enhancing digital literacy. It is essential for educators to incorporate these issues into the curriculum, promoting a critical understanding of social media's influence on identity formation. Furthermore, mental health professionals can utilise these insights to offer targeted support to young women who may be experiencing challenges related to the pressures of digital conformity. The study seeks to

illuminate the broader implications of social media on the mental health of young adults and to offer recommendations for addressing the challenges presented by platforms such as Snapchat. This research focusses on a specific population: 11th-grade female students in government schools in Delhi. It aims to contribute to a deeper understanding of the influence of digital tools on self-esteem and social identity, providing valuable insights for the development of future educational and mental health strategies.

REVIEW OF RELATED LITERATURE

The current body of literature regarding social media and self-esteem highlights the considerable influence that digital platforms exert on users' self-perception. According to Social Comparison Theory, individuals often assess themselves by comparing their appearance, achievements, and abilities with those of others. Within the realm of social media, this comparison is frequently distorted by the application of filters and manipulated images, resulting in unattainable benchmarks of beauty and achievement.

Research conducted by **(Tiggemann and Slater, 2014)** indicates that exposure to altered images on social media is associated with body dissatisfaction, especially in young women. The findings are corroborated by research conducted by **(Fardouly et al., 2015)**, which indicates that the utilisation of photo-editing tools, including those offered by Snapchat, is associated with decreased body satisfaction and increased levels of appearance anxiety.

Moreover, Snapchat filters are engineered to augment facial characteristics in alignment with prevailing societal beauty standards, including enlarging the eyes, smoothing the skin, and slimming the face. These alterations may result in a distorted self-image, as users may start to favour their filtered appearance over their natural look. A study conducted by **(Chae, 2017)** indicates that the preference for an idealised self-image may lead to diminished self-esteem and a heightened dependence on external validation via likes and comments on social media platforms. In addition to influencing self-esteem, Snapchat filters also contribute to the formation of social

identity. Goffman's Theory of Self-Presentation posits that individuals manage their online personas to conform to social expectations and attain acceptance from their peers. Within the framework of Snapchat, this frequently entails the application of filters to align with prevailing beauty standards, potentially resulting in a homogenisation of appearance and a diminishment of individuality.

RESEARCH METHODOLOGY

Aims and Objectives

The primary objective of this research is to examine the impact of Snapchat filters on the social identity and self-esteem of female adults, specifically focussing on 11th-grade students in government institutions in Delhi. The objective of this investigation is to achieve the following aims:

- To investigate the impact of Snapchat filters on students' self-perception and self-esteem.
- To evaluate the relationship between the utilisation of Snapchat filters and the social identity of students, encompassing both their online and offline personas.
- To identify patterns or themes regarding the impact of Snapchat filters on students' psychological well-being and social interactions.

Research Design

This investigation employs a qualitative methodology to achieve a thorough understanding of the individuals involved in the use of Snapchat filters. A phenomenological design was selected to investigate the subjective experiences of 11th-grade female students, facilitating an in-depth analysis of how these filters affect their self-esteem and social identity.

Participants

The research included 17 female students from the 11th grade enrolled in government schools in Delhi. Participants were selected through purposive

sampling to ensure that the sample accurately represented the target population. The criteria for selection included:

- Female students in 11th grade.
- Regular users of Snapchat with experience using its filters.
- Students from government schools in Delhi are expected to maintain consistency in the educational context.

Data Collection Tools

Semi-structured interviews were utilised to collect data, facilitating the examination of participants' experiences. The interview guide comprised open-ended questions aimed at obtaining comprehensive responses regarding:

- The utilisation of Snapchat filters by participants and the motivations behind their usage.
- The participants' perceptions of their appearance prior to and following the application of filters.
- The influence of filters on self-esteem and social identity.
- Investigating perceptions of societal beauty standards and their influence on the utilisation of filters.

The interviews were carried out in a conducive environment to facilitate participants' comfort in sharing their experiences. The duration of each interview was approximately 45-60 minutes, and the sessions were audio-recorded with the consent of the participants.

Data Analysis

Thematic analysis, a method that identifies, analyses, and reports patterns (themes) within qualitative data, were used to analyse the collected data. The data were transcribed verbatim. The subsequent procedures comprised the analysis:

1. **Familiarization with the Data**: Reviewing the transcriptions multiple times to understand the content and context.

2. **Generating Initial Codes**: Identifying and labelling significant features of the data related to self-esteem and social identity.

Ethical Considerations

The study adhered to ethical guidelines to ensure the protection of participants' rights and well-being. Key ethical considerations included:

- **Informed Consent**: Before participating in the study, participants were presented with extensive details regarding the investigation and provided their informed consent.
- **Confidentiality**: All data were kept confidential, and personal identifiers were removed from the transcripts to protect participants' privacy.
- **Voluntary Participation**: Students were permitted to withdraw from the study at any time without incurring any repercussions, and participation was entirely voluntary.

Result and Findings

The findings and results of this study are based on the analysis of semi-structured interviews conducted with 17 female 11th-grade students from government institutions in Delhi. The aim of the study was to investigate the impact of Snapchat filters on the social identity and self-esteem of the participants. The findings suggest the presence of several significant themes related to the psychological effects of Snapchat filters and their use, supported by empirical evidence.

A prominent theme that emerged was the considerable impact of Snapchat filters on self-esteem. A 2023 assessment published by the Pew Research Centre indicates that approximately 68% of teenagers in India utilise Snapchat, with a significant number frequently engaging with filters. This statistic aligns with the findings of the study, in which 82% of the interviewed students indicated daily usage of Snapchat filters. The students reported dissatisfaction with their natural appearance following the use of filters that enhanced their facial features, with 65% acknowledging that they felt more

confident sharing filtered images compared to unfiltered ones. This behaviour is consistent with global trends, as evidenced by a 2022 study conducted by the American Psychological Association, which indicated that frequent use of beauty filters correlates with lower self-esteem and an increased tendency to engage in social comparison.

Another critical finding was the influence of Snapchat filters on social identity. The interviews indicated that 70% of the participants perceived their social media identity, significantly shaped by Snapchat filters, as more attractive than their actual identity. The inclination to adhere to beauty standards propagated by filters resulted in a transformation in participants' perceptions of their social identity, with numerous individuals expressing that their value and acceptance within peer groups were linked to their filtered representations. This dependence on digital enhancements aligns with the findings of a 2022 report by the Royal Society for Public Health, which indicated that 67% of young women experience pressure to conform to the unrealistic beauty standards depicted on social media, resulting in problems such as anxiety and social isolation.

The study underscores the significant influence of Snapchat filters on the psychological well-being of young female students, highlighting the necessity for interventions that tackle the pressures of digital conformity and foster a healthier self-image.

The findings suggest that there are several significant themes related to the psychological effects of Snapchat filters.

1. Impact on Self-Esteem

The research indicated that Snapchat filters have a considerable impact on the self-esteem of participants. A majority of the participants (71%) indicated a reduction in self-esteem when contrasting their unfiltered appearance with their filtered images. Significant observations encompass:

- **Perception of Imperfection**: Participants often reported feelings of inadequacy when their natural appearance diverged from the enhanced, idealised image produced by filters. A significant number of participants indicated that viewing their unfiltered images diminished their feelings of attractiveness and confidence.
- **Dependency on Filters**: A considerable proportion of students reported the regular use of filters, attributing this behaviour to a perception that their natural appearance was inadequate. The dependence on filters was associated with a reduced sense of self-worth, as participants perceived their authentic selves as being less acceptable or less appealing.
- **Negative Feedback**: Several participants indicated that negative feedback on their unfiltered images from peers or social media users exacerbated their diminished self-esteem, thereby reinforcing their inclination to utilise filters.

2. Influence on Social Identity

The research also examined the impact of Snapchat filters on the social identity of the participants. The subsequent findings were identified:

- **Conformity to Beauty Standards**: A significant 82% of participants indicated experiencing pressure to adhere to societal beauty standards as influenced by Snapchat filters. The inclination to showcase an idealised representation of oneself online resulted in changes in the perception and expression of social identity.
- **Online vs. Offline Persona**: Participants reported a notable distinction between their online and offline identities. Individuals frequently experienced a compulsion to curate a filtered persona on social media in order to conform to prevailing beauty ideals, which occasionally contradicted their authentic self-presentation in real life. This discrepancy resulted in confusion regarding their true identity.
- **Social Validation**: The utilisation of filters was associated with a requirement for external validation. A significant number of students reported that positive feedback and likes on curated images were essential for their social validation, subsequently influencing their sense of identity and self-worth.

3. Distorted Self-Image

The research highlighted the potential for Snapchat filters to contribute to a distorted self-image:

- **Preference for Filtered Appearance**: The ongoing utilisation of filters resulted in a preference for the filtered aesthetic in comparison to the natural appearance. Participants indicated that they experienced increased feelings of attractiveness and confidence when filters were applied, resulting in a disconnection between their online and real-life appearances.
- **Impact on Body Image**: The filters often amplified particular traits, such as enlarged eyes or enhanced skin texture, which participants began to perceive as more attractive. This altered perception influenced their body image and self-acceptance, resulting in dissatisfaction with their intrinsic traits.

4. Awareness and Perceptions

Participants' awareness of the impact of filters on their self-esteem and social identity varied:

- **Limited Awareness**: A subset of participants recognised the adverse impacts of filters; however, they expressed a sense of powerlessness to alter their behaviour, attributing this to the omnipresence of social media and the influence of peer pressure. The researchers acknowledged that filters have the potential to establish unrealistic beauty standards, yet they found it challenging to refrain from utilising them.
- **Desire for Authenticity**: Despite the pressures to conform, several participants articulated a desire to embrace their natural appearance and advocate for authenticity in social media representations. The researchers acknowledged the necessity for a more realistic representation of beauty to mitigate the effects of filters.

Discussion

This study underscores the conflict observed in the manner in which filters can offer users transitory gratification (Oliveira et al., 2020) and enhance

confidence (Krause et al., 2019). However, it also indicates that the use of filtration may lead to negative outcomes by generating discrepancies that affect users, thereby providing support for the self-discrepancy theory. The research conducted by Vogel and Rose (2016) demonstrated the adverse effects that result from individuals comparing their actual self-image to the idealised images of others. This research sought to build upon the concept of self-harm by investigating the comparisons drawn between individuals' actual self and their ideal self images. Consequently, it is plausible that women may evaluate themselves with greater scrutiny, leading to the experience of negative emotions and diminished confidence in their own beauty. The findings align with previous studies conducted by Kahn et al. (2020), Shin et al. (2017), Steinsbekk et al. (2021), and Utz et al. (2015). which also highlight the psychological implications associated with the use of Snapchat. It is essential to recognise that the research highlighted the significance of personality and self-confidence in relation to beauty, as these variables affected the degree of the impact. Moreover, Eshiet (2020) indicates that beauty standards are interpreted variably among different participants. Some researchers consider them to be fixed and exclusively used by Snapchat, while others argue that filters reinforce standards that shape individuals' perceptions and reactions to others. This study indicates that the impact of Snapchat filters is confined to the typical inclination towards self-idealization. Women may engage in self-care practices or utilise superficial tools such as Botox or injections; however, it is improbable that they will seek substantial transformations, such as plastic surgery. The objective of this research is to investigate the potential impact of filters on user behaviour, without a specific emphasis on plastic surgery, in contrast to the study conducted by Ramphul and Mejias (2018). This phenomenon may be attributed to the frequent references to faith concerning the approval and contentment of God's creation by the participants.

This research further corroborates the findings of Zhao et al. (2018) concerning the importance of Snapchat filters in challenging the notion of a "authentic" self. This study emphasises the capacity of these filters to modify or improve an individual's appearance, while also recognising that some users

may view them as artificial, unattractive, and misleading. Contrary to the findings of Eshiet's (2020) study, which indicated that filtered images are perceived as more visually appealing than those taken with standard cameras, the current study demonstrates that unaltered "authentic" images of oneself captured with regular cameras or via a mirror are deemed acceptable. This raises questions regarding the underlying reasons for the considerable negative impact that Snapchat's camera settings have exerted on specific users.

Conclusion

The objective of this research is to examine the impact of Snapchat filters on the social identity and self-esteem of female 11th-grade students attending government schools in Delhi. The findings indicate that Snapchat filters significantly influence self-perception and social identity, highlighting the wider implications of digital manipulation tools on the psychological well-being of young adults.

The study emphasises that the utilisation of Snapchat filters, which enable users to modify their physical appearance in images, may result in skewed self-perception among young female adults. The appeal of these filters is rooted in their capacity to generate an idealised representation of the user, which, although initially attractive, may lead to adverse outcomes when individuals start to juxtapose their unfiltered appearance with the digitally augmented images. This comparison frequently results in dissatisfaction with one's natural appearance, contributing to diminished self-esteem and a negative self-image.

Furthermore, the research reveals that these modified perceptions extend beyond the individual, impacting social identity. Social identity, influenced by individuals' self-perception within their peer groups and broader society, becomes interwoven with these digital enhancements. As young women increasingly depend on filters to portray themselves on social media, their social interactions and self-esteem become reliant on sustaining these augmented images. This dependency can establish a detrimental cycle,

wherein the validation obtained from peers for these modified images strengthens the necessity to persist in utilising filters, consequently further alienating their social identity from their authentic selves. This issue is particularly pressing in the context of 11th-grade students in government schools in Delhi. The students, currently at a pivotal phase of identity development, may exhibit vulnerability as a result of the socio-economic and cultural pressures they encounter. The incorporation of Snapchat filters adds an additional dimension of complexity to the development of self-esteem and social identity. The findings of the study indicate that these digital tools may intensify pre-existing insecurities, thereby complicating the ability of these young women to cultivate a positive and authentic self-concept.

The implications of this study are significant, especially for educators and mental health professionals engaged with young adults. The study highlights the necessity for interventions aimed at enhancing digital literacy and fostering critical awareness regarding the influence of social media on self-esteem and identity. Educators can play a crucial role in assisting students in managing the pressures associated with social media by integrating discussions on body image, self-esteem, and the effects of digital tools into the curriculum. Mental health professionals can offer specialised support to individuals experiencing the impacts of these filters, assisting them in developing resilience against the pressures associated with digital conformity. In conclusion, this research underscores the psychological effects of Snapchat filters on young female adults and advocates for an expanded societal dialogue regarding the influence of digital tools on identity formation and self-perception. By addressing these challenges proactively, it is possible to assist young women in developing a healthier relationship with social media, thereby fostering a generation that values authenticity over digital perfection.

Summary of Findings

The research highlights that Snapchat filters have a profound impact on self-esteem, with a majority of participants experiencing a decrease in self-worth when comparing their natural appearance to their filtered images. The study

also reveals that these filters contribute to a shift in social identity, as students feel pressured to conform to societal beauty standards. This pressure often leads to a preference for the idealized appearance presented by filters over their natural selves, resulting in a distorted self-image and a reliance on external validation.

Participants' experiences indicate that the continuous use of filters creates a disconnection between their online and offline personas, causing confusion about their authentic identity. While some students are aware of the negative effects of filters, the pervasive nature of social media and peer pressure often compel them to continue using these tools despite their detrimental impact.

Implications

The findings underscore the need for increased awareness about the psychological effects of social media filters. Educators, parents, and mental health professionals should work together to address these issues by promoting positive self-esteem and encouraging authenticity. Programs and interventions aimed at educating young adults about the potential distortions caused by social media filters can help mitigate their impact on self-perception and social identity.

SUGGESTIONS

The results of this study suggest that there are numerous recommendations that can be implemented to mitigate the effects of Snapchat filters on the social identity and self-esteem of young adults:

1. Educational Programs and Workshops

- **Digital Literacy**: Implement educational programs in schools that focus on digital literacy and the impact of social media on self-esteem and social identity. These programs should include discussions on the nature of digital filters, the effects of unrealistic beauty standards, and strategies for developing a healthy self-image.

- **Workshops for Parents and Educators**: Conduct workshops for parents and educators to help them understand the impact of social media on the mental health of young individuals and provide them with tools to support students in navigating these challenges.

2. Promoting Positive Self-Esteem

- **Encourage Authenticity**: Promote campaigns and initiatives that celebrate natural beauty and encourage individuals to share unfiltered images. This can help counteract the pressures to conform to idealized beauty standards and foster a culture of authenticity.
- **Support Systems**: Develop support systems within schools, such as counselling services and peer support groups, where students can discuss their experiences with social media and receive guidance on building self-esteem.

3. Interventions and Counselling

- **Mental Health Interventions**: Incorporate mental health interventions that mitigate the psychological consequences of social media filters. These may encompass counselling sessions that concentrate on identity, body image, and self-esteem.
- **Self-Reflection Exercises**: Encourage self-reflection exercises that help students understand and appreciate their natural appearance. Techniques such as journaling, positive affirmations, and mindfulness can be effective in building a positive self-image.

4. Research and Development

- **Further Research**: Perform longitudinal research to investigate the enduring impacts of social media filters on self-esteem and social identity. This research can provide deeper insights into the lasting impact of digital tools and inform future interventions.
- **Evaluation of Interventions**: Assess the effectiveness of existing interventions and educational programs aimed at improving self-esteem and

reducing the negative impact of social media. Use the findings to refine and enhance these programs.

Limitations

- **Sample Size**: The generalisability of the findings may be restricted by the limited sample size of 17 participants.
- **Context-Specific Findings**: The study focuses on students from government schools in Delhi, which may not be representative of all female adults or students from different educational contexts.

Recommendations for Future Research

Self-esteem and social identity should be investigated in future research with respect to the long-term effects of Snapchat filters and comparable digital tools.Additionally, studies could investigate the effectiveness of various interventions designed to support positive self-image and resilience among young adults. Understanding how different social media platforms influence psychological well-being can provide a more comprehensive view of the challenges faced by today's digital generation.

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7

JAMA Psychiatry | Original Investigation

Associations Between Time Spent Using Social Media and Internalizing and Externalizing Problems Among US Youth

Kira E. Riehm, MS; Kenneth A. Feder, PhD; Kayla N. Tormohlen, MPH; Rosa M. Crum, MD; Andrea S. Youn
Kerry M. Green, PhD; Lauren R. Pacek, PhD; Lareina N. La Flair, PhD; Ramin Mojtabai, MD

udio Interview

ntal content

ANXIETY

IMPORTANCE Social media use may be a risk fa
However, few longitudinal studies have investig
quantified the proportion of mental health prob
media use.

OBJECTIVE To assess whether time spent using soc
associated with internalizing and externalizing prob

DESIGN, SETTING, AND PARTICIPANTS This longitudin
waves 1 (September 12, 2013, to December 14, 2014),
2015), and 3 (October 18, 2015, to October 23, 2016) c
Tobacco and Health study, a nationally representative
assessed US adolescents via household interviews using
self-interviewing. Data analysis was performed from Jan

EXPOSURES Self-reported time spent on social media duri
minutes, >30 minutes to ≤3 hours, >3 hours to ≤6 hours,

MAIN OUTCOMES AND MEASURE Self-reported past-year inte
externalizing problems alone, and comorbid internalizing an ...ms during
wave 3 using the Global Appraisal of Individual Needs-Short S

RESULTS A total of 6595 adolescents (aged 12-15 years during wave 1; 3400 [51.3%] male) were studied. In unadjusted analyses, spending more than 30 minutes of time on social media, compared with no use, was associated with increased risk of internalizing problems alone (≤30 minutes: relative risk ratio [RRR], 1.30; 95% CI, 0.94-1.78; >30 minutes to ≤3 hours: RRR, 1.89; 95% CI, 1.36-2.64; >3 to ≤6 hours: RRR, 2.47; 95% CI, 1.74-3.49; >6 hours: RRR, 2.83; 95% CI, 1.88-4.26) and comorbid internalizing and externalizing problems (≤30 minutes: RRR, 1.39; 95% CI, 1.06-1.82; >30 minutes to ≤3 hours: RRR, 2.34; 95% CI, 1.83-3.00; >3 to ≤6 hours: RRR, 3.15; 95% CI, 2.43-4.09; >6 hours: RRR, 4.29; 95% CI, 3.22-5.73); associations with externalizing problems were inconsistent. In adjusted analyses, use of social media for more than 3 hours per day compared with no use remained significantly associated with internalizing problems alone (>3 to ≤6 hours: RRR, 1.60; 95% CI, 1.11-2.31; >6 hours: RRR, 1.78; 95% CI, 1.15-2.77) and comorbid internalizing and externalizing problems (>3 to ≤6 hours: RRR, 2.01; 95% CI, 1.51-2.66; >6 hours: RRR, 2.44; 95% CI, 1.73-3.43) but not externalizing problems alone.

CONCLUSIONS AND RELEVANCE Adolescents who spend more than 3 hours per day using social media may be at heightened risk for mental health problems, particularly internalizing problems. Future research should determine whether setting limits on daily social media use, increasing media literacy, and redesigning social media platforms are effective means of reducing the burden of mental health problems in this population.

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JAMA Psychiatry | Original Investigation

Associations Between Time Spent Using Social Media and Internalizing and Externalizing Problems Among US Youth

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Author Audio Interview

Supplemental content

IMPORTANCE Social media use may be a risk factor for mental health problems in adolescents. However, few longitudinal studies have investigated this association, and none have quantified the proportion of mental health problems among adolescents attributable to social media use.

OBJECTIVE To assess whether time spent using social media per day is prospectively associated with internalizing and externalizing problems among adolescents.

DESIGN, SETTING, AND PARTICIPANTS This longitudinal cohort study of 6595 participants from waves 1 (September 12, 2013, to December 14, 2014), 2 (October 23, 2014, to October 30, 2015), and 3 (October 18, 2015, to October 23, 2016) of the Population Assessment of Tobacco and Health study, a nationally representative cohort study of US adolescents, assessed US adolescents via household interviews using audio computer-assisted self-interviewing. Data analysis was performed from January 14, 2019, to May 22, 2019.

EXPOSURES Self-reported time spent on social media during a typical day (none, ≤30 minutes, >30 minutes to ≤3 hours, >3 hours to ≤6 hours, and >6 hours) during wave 2.

MAIN OUTCOMES AND MEASURE Self-reported past-year internalizing problems alone, externalizing problems alone, and comorbid internalizing and externalizing problems during wave 3 using the Global Appraisal of Individual Needs-Short Screener.

RESULTS A total of 6595 adolescents (aged 12-15 years during wave 1; 3400 [51.3%] male) were studied. In unadjusted analyses, spending more than 30 minutes of time on social media, compared with no use, was associated with increased risk of internalizing problems alone (≤30 minutes: relative risk ratio [RRR], 1.30; 95% CI, 0.94-1.78; >30 minutes to ≤3 hours: RRR, 1.89; 95% CI, 1.36-2.64; >3 to ≤6 hours: RRR, 2.47; 95% CI, 1.74-3.49; >6 hours: RRR, 2.83; 95% CI, 1.88-4.26) and comorbid internalizing and externalizing problems (≤30 minutes: RRR, 1.39; 95% CI, 1.06-1.82; >30 minutes to ≤3 hours: RRR, 2.34; 95% CI, 1.83-3.00; >3 to ≤6 hours: RRR, 3.15; 95% CI, 2.43-4.09; >6 hours: RRR, 4.29; 95% CI, 3.22-5.73); associations with externalizing problems were inconsistent. In adjusted analyses, use of social media for more than 3 hours per day compared with no use remained significantly associated with internalizing problems alone (>3 to ≤6 hours: RRR, 1.60; 95% CI, 1.11-2.31; >6 hours: RRR, 1.78; 95% CI, 1.15-2.77) and comorbid internalizing and externalizing problems (>3 to ≤6 hours: RRR, 2.01; 95% CI, 1.51-2.66; >6 hours: RRR, 2.44; 95% CI, 1.73-3.43) but not externalizing problems alone.

CONCLUSIONS AND RELEVANCE Adolescents who spend more than 3 hours per day using social media may be at heightened risk for mental health problems, particularly internalizing problems. Future research should determine whether setting limits on daily social media use, increasing media literacy, and redesigning social media platforms are effective means of reducing the burden of mental health problems in this population.

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For adolescents in the United States, social media use is ubiquitous. A 2018 Pew Research Center poll found that 97% of adolescents report using at least 1 of the 7 most popular social media platforms (YouTube, Instagram, Snapchat, Facebook, Twitter, Tumblr, and Reddit). Moreover, digital media use by adolescents is common: 95% report owning or having access to a smartphone, and almost 90% report they are online at least several times a day.[1]

Social media offers numerous potential benefits to users, including exposure to current events, interpersonal connection, and enhancement of social support networks.[2] However, concerns are increasingly raised about potential harms of social media use.[2] One-quarter of adolescents think social media has a mostly negative influence on people their age, pointing to reasons like rumor spreading, lack of in-person contact, unrealistic views of others' lives, peer pressure, and mental health issues.[1]

An increasing body of literature suggests that social media use is associated with mental health problems in adolescence. Numerous cross-sectional studies and a limited number of longitudinal studies suggest that high levels of social media use are associated with internalizing problems, including depressive and anxiety symptoms,[3-6] although results are not entirely consistent.[7] Some studies also suggest an association between social media use and externalizing problems, such as bullying and attention problems.[8,9] Furthermore, a previous study[4] produced mixed results regarding the possible moderating effect of sex.

The prevalence of major depressive disorder and depressive symptoms has increased among adolescents in the United States,[10,11] and adolescent suicide death and attempt rates have increased sharply during the past 2 decades.[12,13] Some authors[14] have postulated that increases in depression may be attributable to rapid increases in social media use. However, evidence of this association in nationally representative samples is scarce, and little is known about whether reducing time spent on social media might influence the prevalence of mental health problems at a national level.

In this article, we build on existing literature by examining the prospective association of time spent on social media with internalizing and externalizing problems in a representative sample of US adolescents. We used data from the Population Assessment of Tobacco and Health (PATH) study, which is a nationally representative, longitudinal cohort of adolescents.[15] Unlike a prior study,[16] we adjusted for mental health problems measured before the exposure, which is critical for reducing the influence of reverse causality. We hypothesized that greater time spent on social media would prospectively be associated with internalizing and externalizing problems alone, as well as comorbid problems at 1-year follow-up. On the basis of past research,[5] we also examined whether these associations differed between males and females.

Methods

Participants

In this longitudinal cohort study, participants were drawn from the public-use data files of waves 1 (September 12, 2013, to December 14, 2014), 2 (October 23, 2014, to October 30, 2015), and 3 (October 18, 2015, to October 23, 2016) of the PATH study.[15] The methods of the PATH study have been previously described.[15] In brief, the target population for this survey was the civilian household population in the United States. Data were collected in 1-year intervals, starting with wave 1 from September 12, 2013, to December 14, 2014. Multistage-stratified sampling was used to obtain a sample of households from which up to 2 individuals aged 12 to 17 years were randomly selected to be interviewed. Data analysis was performed from January 14, 2019, to May 22, 2019. After oral parent permission and adolescent assent were obtained, adolescents were interviewed using audio computer-assisted self-interviewing. The current analyses were considered exempt from human subjects research according to Johns Hopkins institutional review board policy because the data were publicly available and deidentified.

The weighted response rate for adolescents during wave 1 was 78.4%, and the weighted retention rate during wave 3 was 83.3%.[17] A total of 7595 adolescents (aged 12-15 years during wave 1, aged 13-16 years during wave 2, and aged 14-17 years during wave 3) completed all 3 PATH survey waves. Of these, 1000 adolescents (13.2%) were excluded because they were missing data on at least 1 variable required for this analysis; the remaining 6595 adolescents comprised the analytic sample (eFigure in the Supplement).

Key Points

Question Is time spent using social media associated with mental health problems among adolescents?

Findings In this cohort study of 6595 US adolescents, increased time spent using social media per day was prospectively associated with increased odds of reporting high levels of internalizing and comorbid internalizing and externalizing problems, even after adjusting for history of mental health problems.

Meaning Adolescents who spend more than 3 hours per day on social media may be at heightened risk for mental health problems, particularly internalizing problems.

Measures

Outcome (Wave 3)

Past-year mental health problems, the outcome of interest, were assessed during wave 3 using the Global Appraisal of Individual Needs-Short Screener (GAIN-SS).[18] The GAIN-SS is a screening measure intended to identify a probable mental health disorder and assess symptom severity; it has been validated in adolescents[19] and includes internalizing and externalizing subscales (eTable 1 in the Supplement). Each item measures 1 symptom; for this study, symptoms were considered to be present if the respondent selected in the past month or 2 to 12 months from the response options that indicated the last time they had experienced that symptom. Symptom counts were generated for each subscale. Adolescents were classified as reporting low to moderate (0-3 symptoms) or high (≥4 symptoms) internalizing and externalizing problems. These cut

Figure 1. Directed Acyclic Graph of the Hypothesized Associations Between Study Variables and Waves of Measurement for the Exposure, Outcome, and Potential Confounders

The dashed lines represent potential confounding. The solid line represents the main association of interest. BMI indicates body mass index.

points have been validated for use when making treatment decisions[18] and have previously been used with the PATH sample.[20,21] We combined these subscales to create a single outcome variable with 4 mutually exclusive categories: no or low internalizing and externalizing problems, internalizing problems alone, externalizing problems alone, and comorbid internalizing and externalizing problems. Comorbid problems were defined as having all 4 internalizing and 4 or more externalizing symptoms.

Exposure (Wave 2)

The exposure of interest was time spent using social media per day during wave 2. Adolescents who reported that they ever went online were asked, "Sometimes people use the internet to connect with other people online through social networks like Facebook, Google Plus, YouTube, MySpace, Linkedin, Twitter, Tumblr, Instagram, Pinterest, or Snapchat. This is often called 'social media.' Do you have a social media account?" Adolescents who reported that they had a social media account that they visited were asked, "On a typical day, about how much total time do you spend on social media sites?" The response options were up to 30 minutes; more than 30 minutes, up to 3 hours; more than 3 hours, up to 6 hours; and more than 6 hours. We retained these categories for our exposure variable, with an additional category of none for adolescents who reported not going online, not having a social media account, or never visiting their social media account.

Covariates (Wave 1)

Potential confounders, including demographic characteristics (ie, sex, age, race, and parental educational level), body mass index (based on parent-reported weight and height), self-reported lifetime marijuana use and alcohol use, and scale scores for lifetime internalizing and externalizing problems, were adjusted for in the analyses. To ensure that we did not improperly adjust for mediating variables,[22] we used covariates measured at wave 1 instead of wave 2. The full study design is displayed in **Figure 1**.

Statistical Analysis

Multinomial logistic regression was used to estimate the associations between time spent on social media per day with internalizing problems alone, externalizing problems alone, and comorbid internalizing and externalizing problems (reference group: no or low internalizing and externalizing problems). Both unadjusted and adjusted analyses were conducted. Regression coefficients were exponentiated for interpretation as relative risk ratios (RRRs). In addition, we used the adjusted model to generate and plot predicted probabilities of high internalizing and externalizing problems for each level of social media use for an otherwise average study participant.

We tested for the presence of a linear trend in the coefficients for social media use in their relation to each category of mental health problems by converting the social media use variable to an ordinal variable and reestimating the adjusted model (ie, a Mantel test for trend[23]). A linear trend would suggest that more time spent on social media is associated with a proportionally greater likelihood of reporting mental health problems.

We tested whether any observed association of social media use with mental health problems differed between males and females by testing an interaction term between social media use and sex in our adjusted model.

In addition, we estimated the respective proportions of high internalizing and high externalizing problem cases that would be potentially prevented if adolescents spent less time using social media (ie, the population-attributable fraction [PAF] for social media use). We did this for 4 counterfactual scenarios that represented increasingly greater population reductions in social media use. In scenario 1, adolescents who actually used social media more than 6 hours per day would instead use social media more than 3 hours to 6 hours or less per day; in scenario 2, adolescents who actually used social media more than 3 hours per day would instead use social media more than 30 minutes to 3 hours or less per day; in scenario 3, adolescents who actually used social media more than 30 minutes per day would instead use social media 30 minutes or less per day; and in scenario 4, adolescents who actually spent any amount of time on social media per day would instead not spend any time on social media.

We estimated each scenario by generating a counterfactual population from our adjusted model using the approach to calculate PAFs described by Greenland and Drescher[24] and Rückinger et al.[25] See the eMethods in the Supplement for a detailed description.

To test whether our results were sensitive to missing data, we repeated analyses using multiply imputed data. We performed multiple imputation using chained equations and recomputed the unadjusted, adjusted, and sex-interaction mod-

Table 1. Descriptive Statistics of Population Characteristics for US Adolescents in the PATH Study, 2013-2016, Overall and by Internalizing and Externalizing Problems[a]

Variable	Total Sample (N = 6595)	Internalizing Problems Alone During Wave 3 (n = 611)	Externalizing Problems Alone During Wave 3 (n = 885)	Internalizing and Externalizing Problems During Wave 3 (n = 1169)
Time spent on social media per day during wave 2				
None	1125 (16.8)	73 (6.6)	122 (12.4)	122 (10.7)
≤30 min	2082 (31.8)	172 (7.8)	287 (14.4)	283 (13.6)
>30 min to ≤3 h	2000 (30.7)	198 (9.8)	310 (15.5)	390 (19.6)
>3 to ≤6 h	817 (12.3)	98 (11.9)	97 (12.2)	202 (24.6)
>6 h	571 (8.4)	70 (12.1)	69 (12.7)	172 (29.7)
Sex				
Male	3400 (51.3)	180 (5.0)	564 (17.3)	423 (12.5)
Female	3195 (48.7)	431 (13.4)	321 (10.5)	746 (23.1)
Race				
White only	4563 (70.9)	431 (9.3)	635 (14.5)	831 (18.3)
Black only	1000 (14.8)	69 (6.9)	131 (13.4)	147 (15.0)
Other[b]	1032 (14.3)	111 (10.2)	119 (12.3)	191 (17.2)
Parental educational level				
Less than high school	1308 (17.0)	116 (8.7)	137 (11.0)	183 (14.4)
High school or equivalent	1218 (17.8)	140 (11.5)	133 (11.0)	217 (18.1)
Some college or associate's degree	2072 (31.0)	202 (9.4)	290 (14.3)	417 (19.9)
Bachelor's degree	1296 (21.8)	103 (8.1)	199 (15.7)	232 (17.1)
Advanced degree	701 (12.5)	50 (6.9)	126 (18.7)	120 (16.9)
Age, y				
12-14	4913 (74.2)	443 (8.9)	662 (14.0)	888 (17.8)
15-17	1682 (25.8)	168 (9.5)	223 (13.9)	281 (17.4)
BMI, mean (SD)	21.91 (5.03)	22.30 (5.25)	21.53 (4.57)	22.18 (5.09)
Lifetime alcohol use				
No	4661 (70.0)	410 (8.6)	590 (13.4)	688 (14.5)
Yes	1934 (30.0)	201 (10.2)	295 (15.5)	481 (25.1)
Lifetime marijuana use				
No	6132 (93.3)	561 (8.9)	826 (14.1)	1062 (17.3)
Yes	463 (6.7)	50 (11.2)	59 (12.8)	107 (23.1)
No. of lifetime internalizing problems, mean (SD)	2.19 (1.57)	2.84 (1.37)	2.38 (1.44)	3.19 (1.23)
No. of lifetime externalizing problems, mean (SD)	3.22 (2.12)	3.33 (1.94)	4.09 (1.85)	4.49 (1.78)

Abbreviations: BMI, body mass index (calculated as weight in kilograms divided by height in meters squared); PATH, Population Assessment of Tobacco and Health.

[a] Data are presented as number (percentage) of patients unless otherwise indicated. Percentages, means, and SDs are weighted using the wave 3 all-waves replicate weights. All variables were measured during wave 1 except time spent on social media per day, which was measured during wave 2.

[b] The other race category includes participants identifying as American Indian or Alaska Native, Asian Indian, Chinese, Filipino, Japanese, Korean, Vietnamese, other Asian, Native Hawaiian, Guamanian or Chamorro, Samoan, and other Pacific Islander.

els. We stratified by sex and generated 10 imputed data sets to account for the hypothesized interaction between sex and social media use.[26]

Data for analyses were weighted to be representative of 12- to 15-year-old adolescents living in the United States in 2013 to 2014. Standard errors were estimated using the wave 3 all-waves replicate weights constructed using balanced repeated replication (the Fay method) provided in the PATH data set. Statistical significance was assessed at a 2-sided $P < .05$ level. All analyses were conducted using Stata, version 14 (StataCorp).

Results

Sample Characteristics

A total of 6595 adolescents (aged 12-15 years during wave 1; 3400 [51.3%] male) were included in the analysis. During wave 3, of the sample of 6595 adolescents, 611 (9.1%) reported internalizing problems alone, 885 (14.0%) reported externalizing problems alone, 1169 (17.7%) reported comorbid internalizing and externalizing problems, and the remaining 3930 (59.3%) reported no or low problems. During wave 2, a total of 1125 adolescents (16.8%) reported no social media use, 2082 (31.8%) reported 30 minutes or less, 2000 (30.7%) reported more than 30 minutes to 3 hours or more, 817 (12.3%) reported more than 3 hours to 6 hours or less, and 571 (8.4%) reported more than 6 hours of use per day. Sample characteristics are given in **Table 1**.

Association Between Social Media Use and Mental Health Problems

Compared with adolescents who did not use social media, the use of social media for more than 30 minutes per day was associated with greater risk of internalizing problems alone (≤30

Table 2. Unadjusted and Adjusted RRRs for Each Category of Social Media Use Associated With Internalizing and Externalizing Problems Among 6595 US Adolescents in the PATH Study, 2013-2016[a]

	Internalizing Problems Alone		Externalizing Problems Alone		Comorbid Internalizing and Externalizing Problems	
Variable	RRR (95% CI)	aRRR (95% CI)	RRR (95% CI)	aRRR (95% CI)	RRR (95% CI)	aRRR (95% CI)
Time spent on social media per day during wave 2						
None	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]
≤30 min	1.30 (0.94-1.78)	1.23 (0.89-1.71)	1.28 (0.98-1.67)	1.18 (0.89-1.56)	1.39 (1.06-1.82)	1.27 (0.97-1.67)
>30 min to ≤3 h	1.89 (1.36-2.64)	1.37 (0.96-1.94)	1.60 (1.16-2.21)	1.37 (0.98-1.92)	2.34 (1.83-3.00)	1.59 (1.23-2.05)
>3 to ≤6 h	2.47 (1.74-3.49)	1.60 (1.11-2.31)	1.36 (0.97-1.90)	1.22 (0.86-1.72)	3.15 (2.43-4.09)	2.01 (1.51-2.66)
>6 h	2.83 (1.88-4.26)	1.78 (1.15-2.77)	1.59 (1.07-2.37)	1.40 (0.90-2.19)	4.29 (3.22-5.73)	2.44 (1.73-3.43)
Sex						
Male	NA	0.38 (0.30-0.47)	NA	1.25 (1.03-1.53)	NA	0.51 (0.43-0.61)
Female	NA	1 [Reference]	NA	1 [Reference]	NA	1 [Reference]
Race						
White only	NA	1 [Reference]	NA	1 [Reference]	NA	1 [Reference]
Black only	NA	0.65 (0.50-0.83)	NA	0.86 (0.67-1.10)	NA	0.70 (0.54-0.91)
Other[b]	NA	1.00 (0.73-1.36)	NA	0.85 (0.67-1.09)	NA	0.86 (0.68-1.09)
Parental educational level						
Less than high school	NA	1 [Reference]	NA	1 [Reference]	NA	1 [Reference]
High school or equivalent	NA	1.38 (1.05-1.82)	NA	0.99 (0.75-1.31)	NA	1.23 (0.93-1.63)
Some college or associate's degree	NA	1.17 (0.90-1.51)	NA	1.29 (1.02-1.63)	NA	1.37 (1.08-1.75)
Bachelor's degree	NA	0.99 (0.72-1.34)	NA	1.34 (0.99-1.81)	NA	1.18 (0.89-1.57)
Advanced degree	NA	0.89 (0.60-1.32)	NA	1.69 (1.24-2.31)	NA	1.28 (0.91-1.79)
Age, y						
12-14	NA	1 [Reference]	NA	1 [Reference]	NA	1 [Reference]
15-17	NA	0.94 (0.77-1.14)	NA	0.94 (0.79-1.12)	NA	0.82 (0.70-0.96)
BMI	NA	1.00 (0.98-1.02)	NA	0.99 (0.97-1.00)	NA	1.00 (0.98-1.01)
Lifetime alcohol use						
No	NA	1 [Reference]	NA	1 [Reference]	NA	1 [Reference]
Yes	NA	1.02 (0.84-1.25)	NA	0.97 (0.82-1.14)	NA	1.17 (1.00-1.36)
Lifetime marijuana use						
No	NA	1 [Reference]	NA	1 [Reference]	NA	[1 [Reference]
Yes	NA	0.94 (0.65-1.37)	NA	0.67 (0.47-0.95)	NA	0.71 (0.54-0.95)
Lifetime internalizing problems	NA	1.57 (1.45-1.71)	NA	1.00 (0.93-1.07)	NA	1.48 (1.38-1.60)
Lifetime externalizing problems	NA	0.97 (0.91-1.03)	NA	1.43 (1.35-1.51)	NA	1.36 (1.27-1.44)

Abbreviations: aRRR, adjusted relative risk ratio; BMI, body mass index (calculated as weight in kilograms divided by height in meters squared); NA, not applicable; PATH, Population Assessment of Tobacco and Health; RRR, relative risk ratio.

[a] The aRRRs are adjusted for all covariates listed in Table 1. The reference category is no internalizing or externalizing problems. All variables were measured during wave 1 except time spent on social media per day, which was measured during wave 2.

[b] The other race category includes participants identifying as American Indian or Alaska Native, Asian Indian, Chinese, Filipino, Japanese, Korean, Vietnamese, other Asian, Native Hawaiian, Guamanian or Chamorro, Samoan, and other Pacific Islander.

minutes: RRR, 1.30; 95% CI, 0.94-1.78; >30 minutes to ≤3 hours: RRR, 1.89; 95% CI, 1.36-2.64; >3 to ≤6 hours: RRR, 2.47; 95% CI, 1.74-3.49; >6 hours: RRR, 2.83; 95% CI, 1.88-4.26) and comorbid internalizing and externalizing problems (≤30 minutes: RRR, 1.39; 95% CI, 1.06-1.82; >30 minutes to ≤3 hours: RRR, 2.34; 95% CI, 1.83-3.00; >3 to ≤6 hours: RRR, 3.15; 95% CI, 2.43-4.09; >6 hours: RRR, 4.29; 95% CI, 3.22-5.73) (**Table 2**). In the adjusted model, the associations for the 2 highest categories of social media use persisted for internalizing problems alone (>3 to ≤6 hours: RRR, 1.60; 95% CI, 1.11-2.31; >6 hours: RRR, 1.78; 95% CI, 1.15-2.77), and the associations for the 3 highest categories of social media use persisted for comorbid internalizing and externalizing problems (>30 minutes to ≤3 hours: RRR, 1.59; 95% CI, 1.23-2.05; >3 to ≤6 hours: RRR, 2.01; 95% CI, 1.51-2.66; >6 hours: RRR, 2.44; 95% CI, 1.73-3.43). In contrast, in unadjusted analyses, the association of social media use with externalizing problems was inconsistent (≤30 minutes: RRR, 1.28; 95% CI, 0.98-1.67; >30 minutes to ≤3 hours: RRR, 1.60; 95% CI, 1.16-2.21; >3 to ≤6 hours: RRR, 1.36; 95% CI, 0.97-1.90; >6 hours: RRR, 1.59; 95% CI, 1.07-2.37) and not significant in the adjusted analysis (≤30 minutes: RRR, 1.18; 95% CI, 0.89-1.56; >30 minutes to ≤3 hours:

RRR, 1.37; 95% CI, 0.98-1.92; >3 to ≤6 hours: RRR, 1.22; 95% CI, 0.86-1.72; >6 hours: RRR, 1.40; 95% CI, 0.90-2.19) (Table 2). The predicted probabilities of high internalizing, externalizing, and comorbid problems for each level of social media use, with all other covariates set to their mean, are displayed in **Figure 2**.

We observed a significant linear trend in the coefficients for both internalizing ($F_{1,99}$ = 8.86, P = .004) and comorbid problems ($F_{1,99}$ = 35.16, P < .001); as time on social media increased, the odds of these outcomes increased proportionately. In contrast, we observed no association for externalizing problems ($F_{1,99}$ = 2.25, P = .14).

We observed no statistically significant interaction between social media use and sex for internalizing ($F_{4,96}$ = 0.84, P = .50), externalizing ($F_{4,96}$ = 0.32, P = .86), or comorbid problems ($F_{4,96}$ = 0.73, P = .57).

All PAF estimates are given in **Table 3**. On the basis of our adjusted model assuming no confounding, 0.8% to 18.9% of internalizing problems and 0.8% to 15.3% of externalizing problems could be prevented if participants had instead used less social media.

Results of analyses using multiple imputation methods did not differ appreciably from the main analyses (eTable 2 in the Supplement).

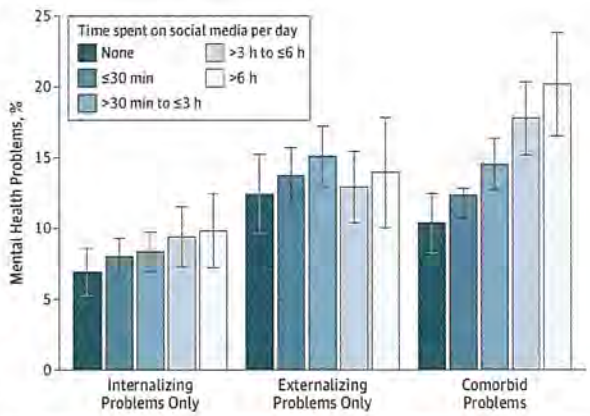
Discussion

Consistent with a prior study,[4] we found that adolescent social media use was prospectively associated with increased risk of comorbid internalizing and externalizing problems as well as internalizing problems alone. This association remained significant after adjusting for demographics, past alcohol and marijuana use, and, most importantly, a history of mental health problems, which mitigates the possibility that reverse causality explains these findings. In contrast, we did not find an association of social media use with externalizing problems alone. This finding suggests that the association of social media use with comorbid problems occurs primarily because of the association of social media with internalizing problems and the high comorbidity of internalizing and externalizing problems. Unlike a prior study,[4] we found no evidence of moderation by sex, perhaps because of the simplicity of our social media use variable, which could not capture the nature of interactions on social media that may differ by sex.

Numerous mechanisms could account for the association between social media use and internalizing problems. Adolescents who engage in high levels of social media use may experience poorer quality sleep, which may be a mediator on the pathway to internalizing problems.[27] Time spent on social media may increase the risk of experiencing cyberbullying, which has a strong association with depressive symptoms.[28] Social media may also expose adolescents to idealized self-presentations that negatively influence body image and encourage social comparisons.[4] Poor emotion regulation and lack of social interaction may also be associated with social media use and contribute to symptoms of anxiety and depression.[29]

These mechanisms are potentially consistent with the notion that spending less time on social media may contribute to mental health. In fact, the PAFs obtained in our study suggest that if adolescents using social media for more than 30 minutes per day had instead used it for 30 minutes or less, there would have been 9.4% fewer high internalizing problem cases and 7.3% fewer high externalizing problem cases. Of importance, this is not meant to imply that reductions in mental health problems would definitively happen if social media use

Figure 2. Adjusted Proportion of Internalizing Problems, Externalizing Problems, and Comorbid Internalizing and Externalizing Problems Stratified by Category of Time Spent on Social Media per Day Among US Adolescents in the Population Assessment of Tobacco and Health Study, 2013-2016



Error bars indicate 95% CIs.

Table 3. Estimated Percentages of Adolescent Mental Health Problem Cases Eliminated in Each Counterfactual Scenario of Time Spent on Social Media[a]

Amount of Time Spent on Social Media per Day	Cases, % (95% CI) Internalizing Only	Externalizing Only	Comorbid	All Internalizing	All Externalizing
No more than					
6 h	0.2 (0.2 to 0.2)	0.4 (0.3 to 0.4)	1.2 (1.1 to 1.2)	0.8 (0.8 to 0.9)	0.8 (0.8.0.9)
3 h	2.3 (2.2 to 2.4)	−3.0 (−3.1 to −2.9)	5.5 (5.3 to 5.6)	4.4 (4.3 to 4.5)	1.7 (1.6 to 1.8)
30 min	3.4 (3.3 to 3.5)	0.7 (0.6 to 0.8)	12.4 (12.2 to 12.7)	9.4 (9.2 to 9.5)	7.3 (7.1 to 7.4)
No time spent on social media	12.7 (12.5 to 12.9)	6.9 (6.7 to 7)	22.0 (21.8 to 22.3)	18.9 (18.7 to 19.1)	15.3 (15.2 to 15.5)

[a] The All Internalizing column includes cases of internalizing only and comorbid internalizing and externalizing problems. The All Externalizing column includes cases of externalizing only and comorbid internalizing and externalizing problems.

were reduced or that all social media use is harmful. Instead, these PAFs suggest the potential influence of our findings on the population at a national level assuming a causal effect of social media use and no confounding—both strong assumptions. Future research could improve on our PAF estimates by using data from randomized clinical trials (RCTs).

Our findings must be balanced with the potential benefits of social media use, which include exposure to current events, communication over geographic barriers, and social inclusion for those who may be otherwise excluded in their day-to-day lives (eg, lesbian, bisexual, transgender, queer, and questioning youth).[2] A limitation of our study is that we measured overall time spent on social media; prior studies[30-32] have found that social media use may be positively or negatively associated with mental health depending on which platforms are used and how. Nevertheless, a number of interventions could lead to a reduction in time spent on social media by adolescents, while still allowing for the benefits of such use. The American Academy of Pediatrics has developed a Family Media Use Plan, which can be tailored to specific developmental phases and help parents set reasonable rules for digital media use.[2] Pediatricians and teachers are essential for promoting these plans, as well as helping parents identify problematic social media use in their children.[33] There is also evidence that interventions that promote media literacy, defined as "specific knowledge and skills that can help critical understanding and usage of the media,"[34(p 455)] counteract the harmful association of media use with behavioral health.[34] Also, there is an increasing movement to improve the design of social media platforms; a notable recent example is not displaying the number of "likes" that an Instagram post receives.[35] We believe that technology companies and regulators responsible for social media platforms should consider how these platforms can be designed to minimize risk of mental health problems.

Some researchers have raised concerns that studies on technology use and well-being are limited by publication bias.[36] We believe that this is a legitimate concern given that many studies on this topic, including the present study, are secondary analyses of data not collected for the purpose of studying social media.[36] There appears to be an urgent need for experimental research, specifically a priori registered RCTs that examine interventions designed to reduce social media use. Our study findings suggest a population-level association between social media use and mental health problems, and evidence from RCTs could build on this by examining changes in mental health as a result of changes in social media use. The existing observational study findings and at least 1 RCT in college students[37] appear to be sufficient to justify investment in these trials. In addition, RCTs may be valuable for developing clinical guidelines and informing regulatory policy for social media design.

Limitations

Some limitations of this study should be noted. First, adolescents self-reported the exposure and outcome, which may inflate the observed associations. Second, we measured mental health problems with a self-report questionnaire rather than a diagnostic interview. Third, the validity of self-reported time spent on social media in the PATH study is unknown. Some research suggests that self-reported time on social media may exceed actual use[38]; future studies should consider the use of digital trace data to capture actual time spent using social media.[39] Fourth, social media use continues to change rapidly over time; although our data were collected relatively recently, they may not reflect current trends. Fifth, although our study design mitigates the possibility of reverse causality, some residual confounding from imprecise measurement of prior mental health problems may have been present. Sixth, it remains possible that mental health problems are prospectively associated with social media use, but we could not examine this in the present study because of data limitations. Seventh, it is possible that the observed associations were an artifact of unmeasured confounding. Although we controlled for a number of potential confounders, there may be others, such as physical activity, that we were unable to include because of data limitations.

Conclusions

This study suggests that increased time spent on social media may be a risk factor for internalizing problems in adolescents. Future research should determine whether setting limits on daily social media use, increasing media literacy, and redesigning social media platforms are effective means of reducing the burden of mental health problems in this population.

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Social Media Use and Internalizing Symptoms in Clinical and Community Adolescent Samples
A Systematic Review and Meta-Analysis

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Supplemental content

IMPORTANCE In response to widespread concerns about social media's influence on adolescent mental health, most research has studied adolescents from the general population, overlooking clinical groups.

OBJECTIVE To synthesize, quantify, and compare evidence on the association between social media use and internalizing symptoms in adolescent clinical and community samples.

DATA SOURCES Peer-reviewed publications from MEDLINE, Web of Science, PsycInfo, and Scopus (initially reviewed in May 2022 and updated in October 2023) and preprints from Europe PubMed Central (February 2023) published in English between 2007 and 2023.

STUDY SELECTION Two blinded reviewers initially identified 14 211 cross-sectional and longitudinal studies quantifying the association between social media use and internalizing symptoms, excluding experimental studies and randomized clinical trials.

DATA EXTRACTION AND SYNTHESIS PRISMA and MOOSE guidelines were followed, pooling data using a random-effects model and robust variance estimation. The quality of evidence was assessed using the Quality of Survey Studies in Psychology Checklist.

MAIN OUTCOMES AND MEASURES Articles were included if they reported at least 1 quantitative measure of social media use (time spent, active vs passive use, activity, content, user perception, and other) and internalizing symptoms (anxiety, depression, or both).

RESULTS The 143 studies reviewed included 1 094 890 adolescents and 886 effect sizes, 11% of which examined clinical samples. In these samples, a positive and significant meta-correlation was found between social media use and internalizing symptoms, both for time spent (n = 2893; *r*, 0.08; 95% CI, 0.01 to 0.15; *P* = .03; I^2, 57.83) and user engagement (n = 859; *r*, 0.12; 95% CI, 0.09 to 0.15; *P* = .002; I^2, 82.67). These associations mirrored those in community samples.

CONCLUSIONS AND RELEVANCE The findings in this study highlight a lack of research on clinical populations, a critical gap considering public concerns about the increase in adolescent mental health symptoms at clinical levels. This paucity of evidence not only restricts the generalizability of existing research but also hinders our ability to evaluate and compare the link between social media use and mental health in clinical vs nonclinical populations.

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Adolescent mental health has declined substantially in recent years. The proportion of UK adolescents (aged 10-24 years)[1] with a probable mental health condition increased from 10% to 25% between 2017 and 2022.[2,3] Globally, 1 in 5 children and adolescents have a mental health condition, most commonly internalizing disorders (eg, anxiety or depression).[4] The impact of such conditions is wide reaching and long lasting, affecting school attendance, interpersonal relationships, employment prospects, physical health, and suicide risk, with suicide now constituting the second-leading cause of death among 15- to 29-year-olds worldwide.[4] Many raise concerns that social media, now ubiquitous (97% of young people are daily users),[5] is accelerating current mental health declines.[6,7]

Scientific research investigating social media's impact on adolescent mental health has failed to provide clarity. There is converging evidence for a small negative cross-sectional association between time spent on social media and well-being.[8-11] However, longitudinal studies and those measuring social media use beyond time spent or mental health beyond general well-being show diverging results.[12-14]

To understand this heterogeneity, researchers have studied whether individual differences (eg, age, sex, or ethnicity) might moderate the relationship between social media use and mental health.[15-18] However, the potential impact of the mental health status of the examined sample has been largely overlooked. Studies routinely recruit adolescents from the general population through schools, universities, or nationally representative surveys.[12-14] While these samples can include individuals experiencing mental health symptoms at clinical levels, they often fail to distinguish them from those experiencing symptoms at subclinical or nonclinical levels.

Individuals with mental health conditions face unique challenges, such as interpersonal or sleep difficulties and educational disruptions.[19] Adolescents with internalizing conditions, in particular, exhibit heightened sensitivity to social comparison and fear of negative evaluation.[20,21] They might therefore use or be impacted by social media differently compared to peers. Failure to account for the nature and severity of mental health indicators could therefore restrict our ability to draw accurate inferences about social media's relationship with mental health.

We addressed the extent and impact of this oversight in 3 steps. First, we completed a preregistered systematic review to quantify the proportion of studies investigating social media use and internalizing symptoms in adolescent clinical samples compared to community or nonclinical samples. Second, we performed a meta-analysis to extract the pooled association between social media use and internalizing symptoms in clinical samples, differentiating between time spent and other measures of social media engagement. Third, we compared the strength and direction of this association across clinical and community samples, testing whether sample type was a moderator.

This work allowed us to gauge whether and how current research in this area of substantial scientific and public interest can be used to make clinically informative recommendations. It also complements preexisting qualitative reviews,[22] synthesizing the quantitative effect sizes in clinical populations and comparing these with community samples. Together, these findings can inform academics by identifying gaps for future research; clinicians, by summarizing research studying relevant populations; and policymakers, by guiding evidence-based decision-making for adolescents at risk.

Key Points

Question What is the proportion of research on the association between social media use and mental health in adolescent clinical populations and does it differ between clinical and community samples?

Findings In this systematic review and meta-analysis of 143 studies, few focused on clinical populations, and these showed a positive association between social media use and internalizing symptoms. These results mirrored findings from community samples.

Meaning The paucity of research on clinical populations limits the generalizability of existing research and hinders a comprehensive evaluation of the association between social media and mental health.

Methods

Search Strategy, Selection, and Extraction

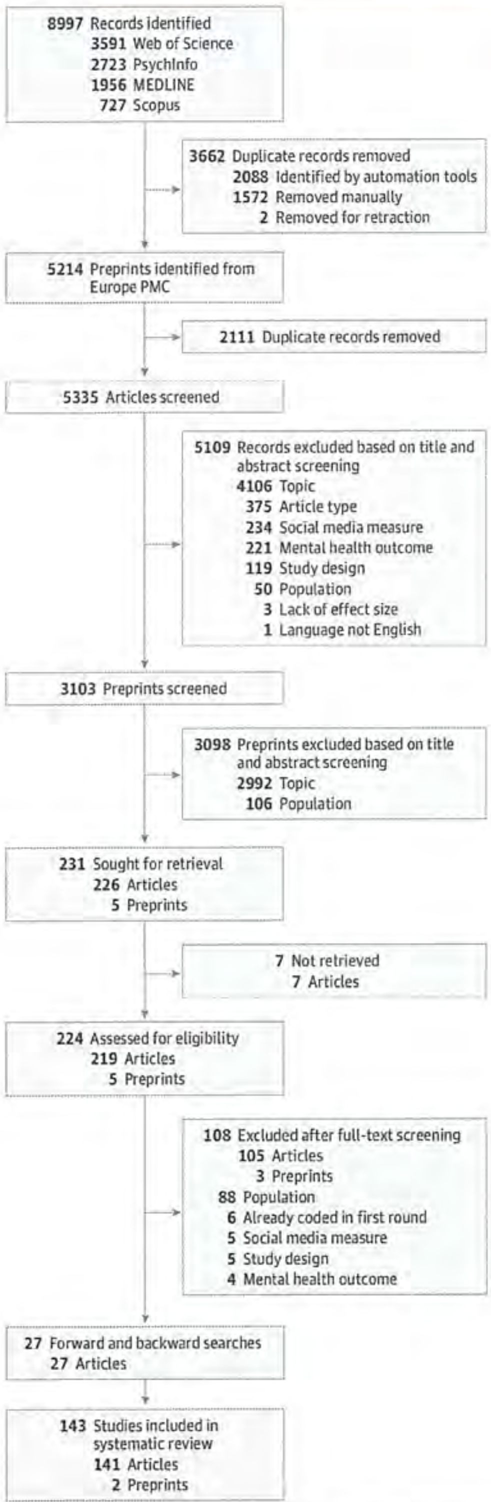
The protocol for this study was preregistered with Prospero (CRD42022321473), following the Preferred Reporting Items for Systematic Reviews and Meta-analyses (PRISMA) reporting guideline. MEDLINE, Web of Science, PsycInfo, and Scopus were searched (eAppendix 1 in Supplement 1) initially in May 2022 and updated in October 2023; forward/backward citation tracing via Google Scholar and preprint search via Europe PubMed Central in February 2023. We identified 14 211 records (8997 articles and 5214 preprints) and 8438 (5335 articles and 3103 preprints) remained after duplicate removal. Considering the nature of the study design, no ethical review was needed.

Selection criteria (eAppendix 2 in Supplement 1) were peer-reviewed English-language articles and preprints published in or after January 2007; quantitative time- or engagement-based social media use measures, self-reported or logged; quantitative symptom-based or other validated questionnaires of anxiety, depression, or both; and adolescent populations aged 10 to 24 years (if not provided: mean age ±1 SD in age range).

In terms of social media, we categorized types of engagement into 6 preregistered categories to allow meaningful description and pooling of studies (eAppendix 2 in Supplement 1): time spent and frequency, activities (eg, messaging and posting), content (eg, exposure to appearance-related content), user perception (eg, impact of likes on mood), active vs passive use, and other.

We categorized study samples into clinical, community or nonclinical. Clinical samples included adolescents who either scored above the clinical threshold on a validated questionnaire, reporting an active diagnosis, accessed mental health services, or were psychiatrically hospitalized. Community samples

Figure 1. Flow Diagram



Reporting of study identification, screening and inclusion for the systematic review. PMC indicates PubMed Central.

included adolescents across the entire distribution of internalizing symptoms without separation into clinical and nonclinical levels, while nonclinical samples excluded adolescents in the clinical range. We restricted our focus to studies that examined internalizing symptoms, excluding other conditions (eg, externalizing or neurodevelopmental) unless they were comorbid with internalizing symptoms.[23]

Following title and abstract screening by 2 independent reviewers, 231 records (226 articles and 5 preprints) remained and were full-text screened (**Figure 1**; eAppendix 3 in Supplement 1). Three independent reviewers double coded 10% of studies to harmonize the coding strategy (eAppendix 4 in Supplement 1; reliability: 95%) and then extracted study information, samples, measures, methodologies, and effect sizes. Risk of bias and quality of studies was assessed using an adapted version of the Quality of Survey Studies in Psychology (eAppendix 5 in Supplement 1).[24]

Statistical Analysis

We completed all analyses in R version 4.1.2 (R Foundation; full list of packages on OSF).[25] We first conducted descriptive analyses of the studies included in the systematic review. Specifically, we calculated the number of studies and effect sizes (with associated percentages), split by sample type, mental health measure, social media measure, social media data collection, study design, and global population (countries were coded based on the International Telecommunications Union classification[26]).

Next, we conducted meta-analyses to test the pooled association between social media use and internalizing symptoms for clinical and community samples. These meta-analyses were restricted to cross-sectional studies and the initial cross-sectional wave of longitudinal studies (see eAppendix 2 in Supplement 1 for details on this choice). Our confirmatory meta-analyses were restricted to studies measuring time spent on social media, to allow meaningful pooling of effect sizes due to measurement similarity, while in the exploratory meta-analyses, we examined measures of social media engagement.

The association was defined as positive when increased social media use was associated with increased internalizing symptoms. We used an a priori statistical significance level of $\alpha = .05$ and interpreted effect sizes in line with Cohen (1988; small: $r < 0.10$, medium: $r = 0.30$, large: $r > 0.50$). For studies reporting effect sizes other than a correlation coefficient, we performed transformations where possible (eAppendix 6 in Supplement 1). We transformed all correlations from Fisher z back to Pearson r for reporting.

We used a random-effects model to calculate summary effect sizes due to the high level of heterogeneity. To account for variance inflation emerging from dependent observations for measures collected from the same participants, we used cluster-robust variance estimation based on the sandwich method with adjusted estimators for small samples and the correlated effects weighting scheme using robumeta ($r = 0.80$ for the within-study effect size correlation).[27-29] Sensitivity analyses showed that using different r values did not affect the inferences made.[25]

Given that longitudinal studies have multiple waves per participant, the meta-analysis included only the effect size from the first wave to minimize variance inflation. However, no differences emerged in the strength and direction when including all waves (eAppendix 7 in Supplement 1).

Risk of Bias Assessment and Moderation

To assess potential bias due to small study effects, including publication bias, we visually inspected funnel plot symmetry and performed the Egger regression test.[30,31] Further, we used a contour-enhanced funnel plot with superimposed areas of statistical significance (corresponding to P = .10, .05, and .01), interpreting an overrepresentation of effect sizes in the highlighted areas as indicative of publication bias.[31] We conducted influence diagnostics (ie, the Cook distance, covariance ratios, and diagonal elements of the hat matrix) using metafor[32] to identify outliers and performed leave-one-out sensitivity analyses with such outliers removed (eAppendix 8 in Supplement 1). To examine heterogeneity in effect sizes, we computed I^2, interpreting values around 25%, 50%, and 75% to indicate low, moderate, and high heterogeneity, respectively.

We conducted 3 preregistered moderator analyses to investigate factors contributing to heterogeneity, namely, sample type (clinical or community samples; nonclinical samples were excluded due to a lack of power), mental health measure (anxiety, depression, or internalizing symptoms) and COVID-19[33-35] (before vs during). We classified studies as happening during the COVID-19 pandemic if any data collection was performed after January 2020.[4] Lastly, we conducted exploratory moderation analyses for age, sex, and the type of social media measure for the meta-analysis on social media engagement.

Results

Systematic Review: Quantifying the Proportion of Clinical Samples

After duplicate removal, we screened 8438 manuscripts (5335 articles and 3103 preprints), including 143 studies in the systematic review (141 articles and 2 preprints; Figure 1). Included studies had a combined sample size of 1 094 890 adolescents (mean, 7657; SD, 40 026; median, 680; minimum, 41; maximum, 388 275) and reported 886 effect sizes for the association between social media use and internalizing symptoms (eAppendix 9 in Supplement 1).

Studies investigating adolescent clinical samples were rare: 11% of effect sizes, corresponding to 99 effect sizes from 12 studies (**Figure 2A**; eAppendix 10 in Supplement 1). Most studies examined community samples (88% of effect sizes; 774 effect sizes from 133 studies), with very few focusing on nonclinical samples (1% of effect sizes; 13 effect sizes from 4 studies). The most common mental health measure was depression (67% of effect sizes; 595 effect sizes from 118 studies), while anxiety (26% of effect sizes; 228 effect sizes from 52 studies) and internalizing symptoms (7% of effect sizes; 63 effect sizes from 16 studies) were less frequently assessed (Figure 2B).

Regarding social media measures, 92% of effect sizes were derived from studies using self-reports (816 effect sizes from 138 studies), while 8% used logged measures (70 effect sizes from 8 studies). Nearly half of the effect sizes were extracted from studies measuring time spent (43%; 381 effect sizes from 91 studies). Less common engagement-based measures included user perception (18%; 160 effect sizes from 36 studies), activity (15%; 131 effect sizes from 31 studies), active vs passive use (7%; 65 effect sizes from 14 studies), content (3%; 29 effect sizes from 4 studies), and other metrics (14%; 120 effect sizes from 21 studies). Most studies (66%; 94 studies) were cross-sectional, while 34% (49 studies) were longitudinal (eAppendix 11 in Supplement 1). In line with previous work,[16] the most commonly studied populations were from the Global North (82%; 117 studies), compared to the Global South (18%; 26 studies).[26]

Overall, approximately half of the included studies (55%; 78 studies) were of acceptable quality based on the Quality of Survey Studies in Psychology Checklist. The remaining 45% (65 studies) were classified as being of questionable quality (eAppendix 5 in Supplement 1).

Meta-Analysis: Quantifying Associations in Clinical Samples

Social Media Time Spent

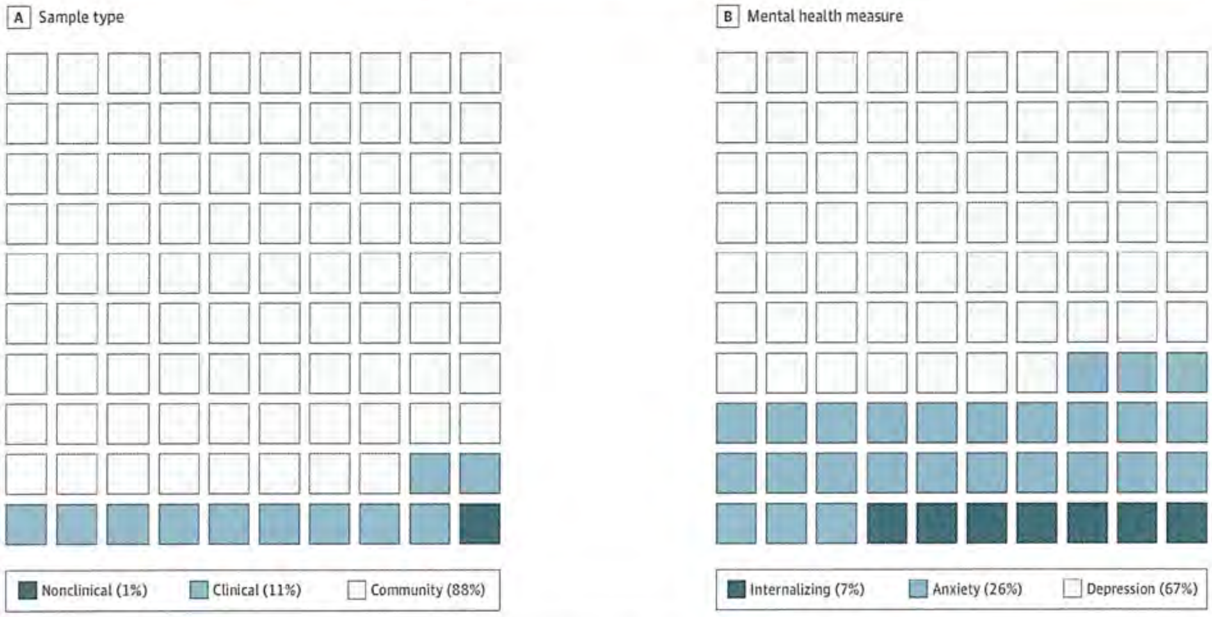
Seven studies of clinical populations (15 effect sizes) measured time spent on social media. The total sample size was 2893 (mean, 413; SD, 585; median, 224; minimum, 49; maximum, 1722). In our confirmatory meta-analysis, we found a positive and significant meta-correlation between time spent on social media and mental health symptoms (r, 0.08; 95% CI, 0.01 to 0.15; P = .03), with moderate heterogeneity (I^2, 57.83) (**Figure 3**[36-42]). Further, the Egger regression test showed no evidence of small study bias (β, −2.19; SE, 0.46; P = .98) (funnel plots in eAppendix 12 in Supplement 1).

Social Media Engagement

The need to move beyond time spent measures of social media use has been widely acknowledged, as these measures are simplistic and fail to distinguish between types of activities or content that can differentially relate to mental health.[43,44] Researchers have therefore advocated for using engagement-based measures, which we examined in an exploratory meta-analysis.

Four studies of clinical populations (19 effect sizes) used engagement-based measures (eAppendix 2 in Supplement 1), specifically social media activities (10 effect sizes; eg, selfie posting) and user perception (9 effect sizes; importance of social media use to daily life), with a total sample size of 859 (mean, 215; SD, 122; median, 233; minimum, 49; maximum, 343). We found a positive and significant meta-correlation between these social media measures and mental health symptoms (r, 0.12; 95% CI, 0.09 to 0.15; P = .002), with high heterogeneity (I^2, 82.67) (**Figure 4**[36-38,40]). Further, the Egger regression test showed no evidence of small study bias (β, −0.55; SE, 0.15; P = .93) (funnel plots in eAppendix 12 in Supplement 1).

Figure 2. Proportion of Included Effect Sizes by Sample Type and Mental Health Measure



Grid of 10 × 10 (100%) squares representing the percentage of literature in the systematic review by sample type and mental health measure. The presented proportion is calculated based on the total number of effect sizes (N = 886).

Meta-Analysis: Comparing Associations Between Clinical and Community Samples

Social Media Time Spent

We also ran a meta-analysis of the 49 studies (and 99 effect sizes) testing community samples (n = 479 215; mean, 9780; SD, 55 482; median, 442; minimum, 41; maximum, 388 275). We found a positive and significant meta-correlation between time spent on social media and internalizing symptoms (r, 0.12; 95% CI, 0.09 to 0.15; $P < .001$) (Figure 3; eAppendix 13 in Supplement 1). This is similar to the meta-correlation found in clinical samples (r, 0.08; 95% CI, 0.01 to 0.15; $P = .03$; I^2, 57.83) but shows higher levels of heterogeneity (I^2, 98.23).

To further test whether sample type influenced the association between time spent on social media and internalizing symptoms, we ran a combined meta-analysis (56 studies with 117 effect sizes; n = 482 273; mean, 8612; SD, 51 926; median, 372; minimum, 41; maximum, 388 275) and tested sample type as a moderator. We found an overall positive meta-correlation across all sample types (r, 0.12, 95% CI, 0.09 to 0.14; $P < .001$; I^2, 98.0) with no evidence of small study bias (β, −0.86; SE, 0.48; $P = .96$) (funnel plots in eAppendix 12 in Supplement 1).

After excluding nonclinical samples due to a lack of power (3 effect sizes from 3 studies), we tested sample type as a moderator (clinical vs community sample). We found nonsignificant results (β, 0.05; SE, 0.03; t, 1.6; 95% CI, −0.02 to 0.12; $P = .145$), and heterogeneity remained high (I^2, 98.0) (Table). Sample type was therefore not considered a key factor explaining differences in the association between time spent on social media and internalizing symptoms among adolescents.

We also tested whether the mental health measure (anxiety, depression, and internalizing symptoms) and COVID-19 (before vs during) were moderators. Neither the mental health measure (depression vs internalizing: β, −0.07; SE, 0.08; t, −0.81; 95% CI, −0.30 to 0.17; $P = .47$; anxiety vs internalizing: β, −0.07; SE, 0.08; t, −0.81; 95% CI, −0.27 to 0.14; $P = .45$) nor COVID-19 (β, 0.04; SE, 0.04; t, 1.16; 95% CI, −0.04 to 0.12; $P = .27$) explained heterogeneity in the meta-correlation between time spent on social media and mental health (Table). There was also no moderation for age or sex (eAppendix 14 in Supplement 1).

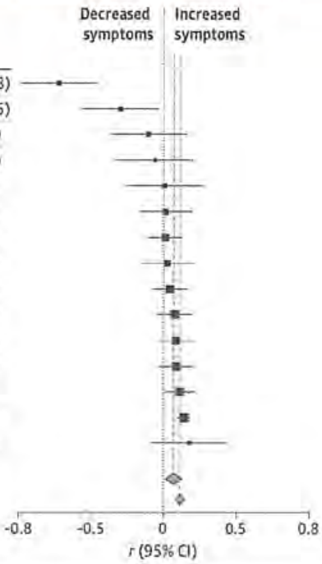
Social Media Engagement

We repeated the same analyses for studies measuring social media engagement. As with the meta-correlation found in clinical samples (r, 0.12; 95% CI, 0.09 to 0.15; $P = .002$; I^2, 82.67), we found a positive and significant association between social media engagement and mental health symptoms (r, 0.14; 95% CI, 0.10 to 0.18; $P < .001$) (Figure 4) in community samples (217 effect sizes from 62 studies; n = 65,799; mean, 1061; SD, 1607; median, 546; minimum, 41; maximum, 10 563). There were high levels of heterogeneity ($I^2 = 94.85$) (eAppendix 13 in Supplement 1).

We included 65 studies with 236 effect sizes in our combined meta-analysis. Across all sample types (n = 68 807; mean, 1,058; SD, 1605; median, 551; minimum, 41; maximum, 10 563), there was a positive meta-correlation between social media engagement and internalizing symptoms (r, 0.14; 95% CI, 0.10 to 0.17; $P < .001$) with high heterogeneity (I^2, 94.63). There was no evidence of small study bias (β, 0.54; SE, 0.67; $P = .22$) also confirmed by

Figure 3. Time Spent on Social Media and Internalizing Symptoms in Clinical Groups

Source	Sample, No.	Platform	Mental health	r (95% CI)
Fardouly et al,[37] 2020	49	Snapchat	Depression	−0.67 (−0.80 to −0.48)
Fardouly et al,[37] 2020	49	Instagram	Anxiety	−0.32 (−0.55 to −0.05)
Fardouly et al,[37] 2020	49	YouTube	Anxiety	−0.11 (−0.38 to 0.17)
Fardouly et al,[37] 2020	49	Snapchat	Anxiety	−0.07 (−0.35 to 0.21)
Fardouly et al,[37] 2020	49	Instagram	Depression	0.01 (−0.28 to 0.29)
Hamilton et al,[38] 2021	100	Any	Anxiety	0.01 (−0.19 to 0.21)
Nesi et al,[35] 2021	243	Any	Internalizing	0.01 (−0.12 to 0.14)
Hamilton et al,[38] 2021	100	Any	Depression	0.02 (−0.18 to 0.22)
Uçar et al,[39] 2018	224	Any	Anxiety	0.04 (−0.09 to 0.17)
Nesi et al,[35] 2021	243	Any	Internalizing	0.08 (−0.05 to 0.20)
Noel et al,[40] 2022	212	Any	Depression	0.09 (−0.05 to 0.22)
Uçar et al,[39] 2018	224	Any	Depression	0.09 (−0.04 to 0.22)
Nesi et al,[36] 2022	343	Any	Internalizing	0.12 (0.01 to 0.22)
Kelly et al,[41] 2019	1722	Any	Depression	0.15 (0.10 to 0.20)
Fardouly et al,[37] 2020	49	YouTube	Depression	0.19 (−0.10 to 0.45)
Model with RVE for clinical samples				0.08 (0.01 to 0.15)
Model with RVE for community samples				0.12 (0.09 to 0.15)



Forest plot for the individual and pooled effect sizes representing the association between time spent on social media and mental health symptoms. Effect sizes for clinical samples are shown both individually (ie, separate rows with author, year, and sample size) and as a pooled estimate (model with cluster-robust variance estimation [RVE]), while the effect size for community samples is only presented as a pooled estimate at the bottom. Individual Pearson *r* coefficients are depicted as filled squares with the size indicating the relative weight, based on sample size, of each effect size estimate for clinical studies in the meta-analysis. Increased time spent on social media was associated with decreased symptoms (to the left of zero) or increased symptoms (to the right of zero). The blue diamond and the dashed line represent the overall summary effect size across all clinical studies (*r*, 0.08; 95% CI, 0.01 to 0.15; $P < .001$), calculated using RVE to account for dependencies between effect sizes coming from the same study. The orange diamond and dashed line represent the overall summary effect size across all studies run on community samples (*r*, 0.12; 95% CI, 0.09 to 0.15; $P < .001$). The error bars and diamond width represent the 95% CIs for the effect sizes. The dotted reference line at $r = 0$ represents the point of reference for no correlation.

visual inspection of the funnel plot (eAppendix 11 in Supplement 1).

Sample type (clinical vs community) was not considered a significant moderator of the overall association between social media engagement and internalizing symptoms (β, 0.01; SE, 0.02; *t*, 0.72; 95% CI, −0.05 to 0.08; $P = .52$), and heterogeneity remained high (I^2, 94.70) (Table). Our additional moderation analyses, summarized in the Table, showed that neither mental health measure (anxiety vs internalizing: β, 0.03; SE, 0.04; *t*, 0.78; 95% CI, −0.11 to 0.17; $P = .49$; depression vs internalizing: β, 0.02; SE, 0.03; *t*, 0.74; 95% CI, −0.08 to 0.12; $P = .53$) nor COVID-19 (β, −0.06; SE, 0.05; *t*, −1.23; 95% CI, −0.15 to 0.04; $P = .24$) explained heterogeneity in the meta-correlation between social media engagement and mental health symptoms. There was also no moderation for the type of social media measures (Table), age, or sex (eAppendix 14 in Supplement 1).

Discussion

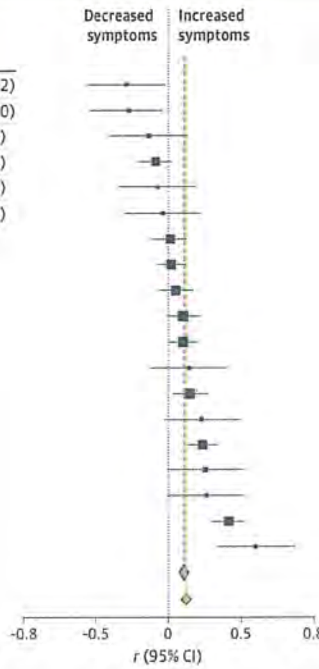
This systematic review and meta-analysis synthesized data from 16 years of research examining the association between social media use and internalizing mental health in more than 1 million adolescents. We found that 11% of studies examined clinical populations, while 88% recruited adolescents from the general population. There was a small, positive, and significant meta-correlation between social media use and internalizing mental health in clinical samples, regardless of whether time- or engagement-based social media metrics were studied. Notably, these meta-correlations did not substantially differ from those found in community samples.

Our first finding highlights a lack of research on clinical populations. Notably, adolescents affected by clinical-level anxiety and depression can face higher social withdrawal, sleep problems, low self-esteem, increased susceptibility to peer influence, and excessive rumination compared to adolescents from the general population.[45] These symptoms may alter their social media interaction and its impact on their mental health.[36,46,47] Hence, the lack of an evidence base in these high-risk populations, resulting in limited investigation of clinically relevant mechanisms, limits our capacity to draw accurate inferences about the relationship between social media use and mental health.

In contrast to the common assumption that clinical populations might show a stronger association between social media use and mental health declines than community samples,[37] we found no substantial differences. This result could be explained by the increasing occurrence of clinically significant symptoms in community samples[3,4] and the diminishing divide between these groups. Alternatively, adolescent clinical populations might adjust their social media use based on their mental health needs, leading to comparable usage patterns and correlations. Lastly, clinical groups could also be experienc-

Figure 4. Social Media Engagement and Internalizing Symptoms in Clinical Groups

Source	Sample, No.	Platform[a]	Mental health	r (95% CI)
Fardouly et al,[37] 2020	49	Activity	Anxiety	−0.30 (−0.54 to −0.02)
Fardouly et al,[37] 2020	49	Activity	Anxiety	−0.28 (−0.52 to −0.00)
Fardouly et al,[37] 2020	49	Activity	Anxiety	−0.14 (−0.41 to 0.15)
Nesi et al,[35] 2021	243	Perception	Internalizing	−0.09 (−0.21 to 0.04)
Fardouly et al,[37] 2020	49	Activity	Depression	−0.08 (−0.35 to 0.21)
Fardouly et al,[37] 2020	49	Activity	Depression	−0.04 (−0.31 to 0.25)
Nesi et al,[35] 2021	243	Perception	Internalizing	0.02 (−0.11 to 0.15)
Nesi et al,[36] 2022	343	Perception	Internalizing	0.03 (−0.08 to 0.14)
Uçar et al,[39] 2018	224	Perception	Anxiety	0.06 (−0.07 to 0.19)
Nesi et al,[35] 2021	243	Perception	Internalizing	0.12 (−0.01 to 0.24)
Nesi et al,[36] 2022	343	Perception	Internalizing	0.12 (0.01 to 0.22)
Fardouly et al,[37] 2020	49	Activity	Depression	0.17 (−0.12 to 0.43)
Uçar et al,[39] 2018	224	Perception	Depression	0.17 (0.04 to 0.29)
Fardouly et al,[37] 2020	49	Activity	Anxiety	0.25 (−0.03 to 0.50)
Nesi et al,[36] 2021	343	Perception	Internalizing	0.26 (0.16 to 0.36)
Fardouly et al,[37] 2020	49	Activity	Depression	0.28 (−0.00 to 0.52)
Fardouly et al,[37] 2020	48	Activity	Depression	0.28 (−0.00 to 0.52)
Nesi et al,[35] 2021	243	Perception	Internalizing	0.43 (0.32 to 0.53)
Fardouly et al,[37] 2020	48	Activity	Anxiety	0.58 (0.36 to 0.74)
Model with RVE for clinical samples				0.12 (0.09 to 0.15)
Model with RVE for community samples				0.14 (0.10 to 0.18)



Forest plot for the individual and pooled effect sizes representing the association between social media engagement and mental health symptoms. Effect sizes for clinical samples are shown both individually (ie, separate rows with author, year, and sample size) and as a pooled estimate (model with cluster-robust variance estimation [RVE]), while the effect size for community samples is only presented as a pooled estimate at the bottom. Individual Pearson *r* coefficients are depicted as filled squares with the size indicating the relative weight, based on sample size, of each effect size estimate for clinical studies in the meta-analysis. Increased social media engagement was associated with decreased symptoms (to the left of zero) or increased symptoms (to the right of zero). The blue diamond and dashed line represent the overall summary effect size across all clinical studies (r, 0.12; 95% CI, 0.09 to 0.15; $P < .001$), calculated using RVE to account for dependencies between effect sizes coming from the same study. The error bars and diamond width represent the 95% CIs. The orange diamond and dashed line represent the overall summary effect size in community samples (r, 0.14; 95% CI, 0.10 to 0.18; $P < .001$). The dotted reference line at $r = 0$ represents the point of reference for no correlation. More information on the type of social media engagement measured in each study is reported in eAppendix 15 in Supplement 1.

[a] All reported measures of social media use are for any platform (no study measured activity or user perception in relation to a specific platform).

ing less variability in mental health symptomatology (eg, ceiling effects), lessening the observable correlations between social media use and mental health symptoms.

Limitations

We underscore some limitations of this work. First, inaccurate self-report measures of social media use[48] might have decreased our ability to locate differences between clinical and community samples even if they existed. Second, while we summarized studies with longitudinal effect sizes and selected control variables as part of our systematic review (eAppendix 11 in Supplement 1), our meta-analysis only included correlations. Hence, no causal inferences can be drawn from the pooled meta-correlation about whether increased social media use leads to higher symptoms or vice versa.

Further, we categorized social media engagement with 5 predefined categories, which are not exhaustive and could mask important nuances. For example, the role of social media content will depend on its nature, which could be positive, negative, or neutral. In addition, we focused on internalizing mental health only. Hence, conclusions cannot be generalized to other conditions. Limiting the inclusion of studies to those published in English may introduce language bias and exclude valuable research conducted in other languages.

Conclusions

The findings in this study demonstrated the moderate to high levels of heterogeneity common to this research area.[13] This variation could potentially be explained by individual differences in demographic characteristics among participants that we did not test, due to the lack of data or statistical power. However, when conducting exploratory moderation analyses for age and sex, we found that neither of those factors explained heterogeneity. We also found no evidence of publication bias.

Many worry about social media's role in increased clinical-level mental health symptoms among adolescents. However, current research falls short of adequately targeting the specific populations required to draw accurate inferences about this matter. Despite our initial findings of a similar association across clinical and community samples, there is still a real risk that we are incorrectly generalizing results from the gen-

Table. Moderation Analyses[a]

Moderator	Level	Studies, No.	Effect sizes, No.	Estimate (SE)	t Value	95% CI	P value
Time spent on social media and internalizing symptoms							
Sample type	Clinical [reference]	7	15	NA	NA	NA	NA
	Community	49	99	0.05 (0.03)	1.6	−0.02 to 0.12	.15
COVID-19	Before [reference]	44	100	NA	NA	NA	NA
	During	9	12	0.04 (0.04)	1.16	−0.04 to 0.12	.27
Mental health measure	Internalizing [reference]	4	5	NA	NA	NA	NA
	Depression	48	69	−0.07 (0.08)	−0.81	−0.30 to 0.17	.47
	Anxiety	19	40	−0.07 (0.08)	−0.81	−0.27 to 0.14	.45
Social media engagement and internalizing symptoms							
Sample type	Clinical [reference]	4	19	NA	NA	NA	NA
	Community	62	217	0.01 (0.02)	0.72	−0.05 to 0.80	.52
COVID-19	Before [reference]	51	196	NA	NA	NA	NA
	During	10	31	−0.06 (0.05)	−1.23	−0.15 to 0.04	.24
Mental health measure	Internalizing [reference]	3	8	NA	NA	NA	NA
	Depression	55	169	0.02 (0.03)	0.74	−0.08 to 0.12	.53
	Anxiety	24	59	0.03 (0.04)	0.78	−0.11 to 0.17	.49
Social media measure	Other [reference]	11	20	NA	NA	NA	NA
	Active vs passive	10	42	0.00 (0.04)	0.02	−0.09 to 0.09	.99
	Activity	22	69	0.05 (0.05)	0.90	−0.07 to 0.17	.38
	Content	2	25	−0.07 (0.04)	- 1.74	−0.34 to 0.19	.27
	Perception	30	80	0.10 (0.05)	2.06	−0.00 to 0.20	.06

Abbreviation: NA, not applicable.

[a] Results of moderation analyses for the meta-correlation of internalizing symptoms with time spent on social media and engagement-based social media use measures.

eral population to young people with mental health conditions. The potential impact of this extends beyond research to clinical practice and policymaking. For clinicians, more research on clinical populations could enrich strategies for patient consultations and family education, allowing for the integration of social media management into treatment plans. For policymakers, it could shape policies for safer social media platforms and funding allocation toward mental health programs. In a world increasingly saturated by digital technology, we cannot afford to design prevention programs, interventions, and regulations without knowing that they work for everyone, especially those who are most vulnerable.

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Concept and design: Fassi, Thomas, Parry, Ford, Orben.
Acquisition, analysis, or interpretation of data: Fassi, Thomas, Parry, Leyland-Craggs.
Drafting of the manuscript: Fassi, Orben.
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Contents lists available at S...

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Associations between ... ...ge variables

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...with body image concerns. Face-altering filters may ...perceptions and cognitions. As no known study has examined these filters ...study investigated the relationship between TikTok facial filter use, facial dissatis- ...body image concern. Participants (N = 397) were undergraduate students reporting TikTok use in the past 2 weeks. Eligible participants completed a battery of surveys relating to social media use and body image. Linear regressions were conducted to examine the association between TikTok facial filter use (appearance-enhancing and goofy filters) and body image outcomes. Significant positive associations were found between both types of filter use and all body image outcomes. However, when both types of filter use were included in the same regression models, appearance-improving filter use remained significant while goofy filter use became non-significant. This is one of the first studies to examine facial filter use and the first to examine this behavior in the context of TikTok. Future researchers should aim to examine these constructs in experimental and/or longitudinal designs to identify temporal ordering of filter usage and body image outcomes to further understanding of this behavior.

1. Introduction

Over the past two decades, social networking sites have quickly become an integral part of many individuals' daily routines—representing salient media sources that may impact users' body image. It is estimated that 90 % of young adults in the U.S. visit at least one social media site per day, with 58 % of teens reporting daily use of TikTok (a video-based social media platform) alone (Lin et al., 2016; Vogels & Gelles-Watnick, 2023). A strong base of research has emerged suggesting that usage of social media is associated with body dissatisfaction and body image concerns (e.g., Cohen et al., 2017; Fardouly & Vartanian, 2016; Holland & Tiggemann, 2016). Body dissatisfaction represents both an economic and public health concern given its financial costs (estimated to be between $226 and $507 billion in 2019) and association with lower quality of life and adverse health outcomes (Bucchianeri & Neumark-Sztainer, 2014; Griffiths et al., 2016; Mond et al., 2013; Yetsenga et al., 2024). Extreme forms of body image concerns – that is body image disorders such as body dysmorphic disorder (BDD) and eating disorders (EDs) – have high prevalence and mortality rates compared to other psychological disorders (Arcelus et al., 2011; Angelakis et al., 2016; Koran et al., 2008; Stice & Shaw, 2002). Thus, it is imperative that researchers further understand the mechanisms that underpin the association between social media use and body image concerns.

One theory that may provide insight into the mechanisms by which social media use and body image concerns are related is the tripartite influence model (Thompson et al., 1999). According to this model, media is one of the primary psychosocial pressures (along with peers and family) that influence the internalization of appearance ideals. As suggested by the tripartite influence model, these pressures simultaneously influence one another and collectively lead to thin and/or muscular ideal internalization, which then leads to body image concerns and disordered eating. Jarman et al. (2021) tested the tripartite influence model in the context of appearance pressures specifically from social media platforms Snapchat and Instagram, finding support for the model when appearance pressures came from social media sites rather than traditional media. As research on social media use and body image (dis) satisfaction accumulates, researchers have highlighted the need to specify what types of social media and what aspects of social media usage may be most closely related to body image outcomes.

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Associations between TikTok facial filter use and body image variables

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ABSTRACT

Research has found social media use to be associated with body image concerns. Face-altering filters may negatively impact appearance-related perceptions and cognitions. As no known study has examined these filters within TikTok, the present study investigated the relationship between TikTok facial filter use, facial dissatisfaction, and body image concern. Participants (N = 397) were undergraduate students reporting TikTok use in the past 2 weeks. Eligible participants completed a battery of surveys relating to social media use and body image. Linear regressions were conducted to examine the association between TikTok facial filter use (appearance-enhancing and goofy filters) and body image outcomes. Significant positive associations were found between both types of filter use and all body image outcomes. However, when both types of filter use were included in the same regression models, appearance-improving filter use remained significant while goofy filter use became non-significant. This is one of the first studies to examine facial filter use and the first to examine this behavior in the context of TikTok. Future researchers should aim to examine these constructs in experimental and/or longitudinal designs to identify temporal ordering of filter usage and body image outcomes to further understanding of this behavior.

1. Introduction

Over the past two decades, social networking sites have quickly become an integral part of many individuals' daily routines—representing salient media sources that may impact users' body image. It is estimated that 90 % of young adults in the U.S. visit at least one social media site per day, with 58 % of teens reporting daily use of TikTok (a video-based social media platform) alone (Lin et al., 2016; Vogels & Gelles-Watnick, 2023). A strong base of research has emerged suggesting that usage of social media is associated with body dissatisfaction and body image concerns (e.g., Cohen et al., 2017; Fardouly & Vartanian, 2016; Holland & Tiggemann, 2016). Body dissatisfaction represents both an economic and public health concern given its financial costs (estimated to be between $226 and $507 billion in 2019) and association with lower quality of life and adverse health outcomes (Bucchianeri & Neumark-Sztainer, 2014; Griffiths et al., 2016; Mond et al., 2013; Yetsenga et al., 2024). Extreme forms of body image concerns – that is body image disorders such as body dysmorphic disorder (BDD) and eating disorders (EDs) – have high prevalence and mortality rates compared to other psychological disorders (Arcelus et al., 2011; Angelakis et al., 2016; Koran et al., 2008; Stice & Shaw, 2002). Thus, it is imperative that researchers further understand the mechanisms that underpin the association between social media use and body image concerns.

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Emerging research suggests that appearance-focused social media is the type of social media use most associated with body image concerns (Cohen et al., 2017). Appearance-focused social media can be any social media content in which the primary focus of the content is image-based or related to aspects of one's appearance. While there are no agreed upon theoretical reasonings for this association, social comparison theory may provide insights (Festinger, 1954). Applied to social media, this theory suggests that users (particularly those who already have body image concerns) may engage in upward appearance comparisons, comparing their appearance and perceived defects with inappropriate or unrealistic appearance ideals, leading to more negative appraisals of their appearance. Indeed, a recent study found that use of TikTok was indirectly related to body dissatisfaction sequentially through upward appearance comparison to others viewed on the app and increased body surveillance (Bissonette Mink & Szymanski, 2022). Further, Jarman et al. (2021) found appearance-focused social media use was uniquely associated with poorer body satisfaction and well-being, rather than social media use in general. While evidence is beginning to accumulate that appearance-focused social media use is closely associated with body image concerns, research has highlighted the importance of further investigation into the specific components of appearance-focused social media use beyond mere exposure that may present the highest risk for body image concerns (Harriger et al., 2023).

One component of social media use that has the potential to impact body image is face-altering filters found on social media platforms such as Snapchat, Instagram, and TikTok. These types of filters are becoming more deeply embedded in many social media platforms and can range from minor alterations, such as smoothing complexion to changing the shape and size of facial features (e.g., reducing the size of the nose, sharpening the jawline, etc.). Face-altering filters may also involve more whimsical changes, including giving the user dog ears or making it appear as though there are butterflies sitting on the user's face. Emerging research concerning the use of face-altering filters has mirrored research on photo-editing behaviors, suggesting that greater usage may be associated with greater body image concerns (Cohen et al., 2018; Hermans et al., 2022; Lamp et al., 2019; McLean et al., 2015; Veldhuis et al., 2020). In a recent experimental design, Dijkslag et al. (2024) determined that exposure to beautifying facial filters on Instagram decreased body satisfaction. However, there is some indication that motivation for using filters may play a role in the impact filter use has on body image concerns. Javornik et al. (2022) found that Instagram filter usage motivated by presenting one's ideal self to viewers was associated with increased filter usage and decreased self-acceptance, while usage for silliness, enjoyment, or social interaction increased positive affect and had no effect on self-acceptance. With literature on face-altering filters still in its nascency, there have been calls for further research into the differences between various social media platforms and the features available on each (Harriger et al., 2023).

Burnell et al. (2022) examined usage of and intention for using similar face-altering filters' association with body image outcomes on Snapchat, another social media platform with a variety of embedded filters called "lenses." In order to examine these constructs, Burnell and colleagues created a novel filter-use scale, which they used in both correlational and experimental designs. Their filter scale included 6 items measuring behaviors and intentions in using face-altering filters. Three item stems were used in this instrument to measure a behavior (e.g., posting a selfie with a filter, sending a selfie with a filter, etc.), with each ending indicating two different intentions: (1) 'to make it look better' and (2) 'to make it look silly.' Despite the theoretical reasoning supporting differences between differentiating intentions, these items all loaded into one factor: Snapchat lens use. They measured this variable's association with several body image constructs (i.e., facial satisfaction, body surveillance, self-objectification, and beauty ideal internalization). The results of their experimental study indicated that those who took more selfies reported higher appearance preoccupation; however, there were no significant differences in body image outcomes between those who used Snapchat lenses in photos and those who did not. The correlational study found significant positive associations between Snapchat lens use and several body image outcomes, namely self-objectification, body surveillance, and beauty-ideal internalization (Burnell et al., 2022). These findings demonstrate a preliminary association between facial filter use and body image concerns; however, further investigation is warranted to see how these findings may extend to other social media platforms.

1.1. The current study

There is a large body of research that has examined different aspects of body image in the context of social media, analyzing time spent on applications, photo editing behavior, and more recently, facial filter usage. While researchers are only beginning to grasp the complexities of how social media behaviors relates to body image, social media sites are quickly moving forward with new features and technologies, the correlates of which are not yet fully understood. Very little research has examined face-altering filters, and research that has done so has primarily focused on Instagram and Snapchat. The current study will explore how this these filters may be associated with body image constructs on TikTok, which has deeply embedded filters in its platform and is among the most widely used and quickly growing social media sites (Doyle, 2024). The current study aims to build upon previous findings examining the association between the type of face-altering filter use and appearance concerns amongst college-aged individuals who use TikTok. The following hypotheses were examined: (H1) There will be a significant, positive association between the use of appearance "improving" face-altering filters and body image concerns, and (H2) a significant, positive association between use of appearance "improving" face-altering filters and facial dissatisfaction. Given the limited literature concerning the use of facial filters for entertainment and its association with body image outcomes, the current study also aims to understand how "goofy" filter (i.e., those which are not intended to improve the user's appearance, but rather to alter it in a silly or whimsical way) usage may be associated with body image concern and facial dissatisfaction; however, no directional hypotheses are made at this time, given the paucity of prior literature on this topic.

2. Methods

2.1. Participants and procedures

Participants were 397 undergraduate students from San Diego State University recruited through an institution-based online research platform (SONA) and through the Canvas pages for undergraduate psychology courses. To take part in the study, participants were required to be at least 18 years old, have used the social media app TikTok in the last two weeks, identify as an undergraduate at San Diego State University, and be able to read and speak English. Participants were provided a brief overview of the details of the study through a digital cover letter, including the goal of the study and their rights as a participant. If participants agreed to take part in the study, they were given a battery of surveys containing demographic questions and measures assessing body image concerns and social media use and behavior. Participants were compensated through SONA and class extra credit.

In total, 397 participants completed the surveys in total; however, 52 participants did not pass two attention checks and were consequently excluded from analyses. There were also five participants who identified as non-binary, but due to the extremely small sample size of this gender group, they were also excluded from analyses. Thus, the final analytic sample size was 340 undergraduate students. Participants were between the ages of 18–41 years old (M_{age} = 20.3, SD = 2.68). Of these participants, 82.6 % identified as cisgender women, 65.2 % identified as White, and 73.6 % identified as heterosexual (See Table 1).

Table 1
Sample characteristics – Frequencies.

Demographic	*N*	%
Sex		
Female	280	82.4%
Male	60	17.6%
Gender		
Woman	281	82.6%
Man	59	17.4%
Sexual Orientation		
Heterosexual/Straight	254	73.6%
Homosexual/Gay/Lesbian	18	4.3%
Bisexual	47	13.6%
Pansexual	12	3.5%
Asexual	5	1.4%
Race		
White	225	65.2%
Black/African American	21	6.1%
Native Hawaiian/Pacific Islander	8	2.3%
Native American/Indigenous	12	3.5%
Asian	55	15.9%
Hispanic/Latino	112	32.5%
Perceived Weight Status		
Very underweight	3	0.9%
A little underweight	36	10.6%
Neither underweight or overweight	209	61.5%
A little overweight	73	21.5%
Very overweight	19	5.6%

2.2. *Measures*

2.2.1. *Facial filter use*

Participants completed the TikTok Filter Use Scale (TFUS), an author-developed six-item survey that measures behavior on the platform (i.e., frequency of filter use, type of use, and type of filter). This instrument includes questions that ask about respondents' intentions of using filters in posted content and their filter-seeking behaviors. To account for different intentions of using a filter, six items were asked with the same stem containing a behavior, but with different endings indicating two intentions: to "look goofy," and to "look more attractive." This was inspired by the scale used in Burnell and colleagues' (2022) study examining Snapchat lenses. Participants were asked to rate their behavior on a 5-point Likert scale ranging from 1 (*Never*) to 5 (*Always*). Exploratory factor analysis suggested that a two factor, four-item structure was more appropriate based on the data used in the present study and theoretical reasoning, so the final scale used was comprised of two subscales (appearance-focused filter use and goofy filter use), each with two items. Item scores for each subscale were averaged to derive each subscale score. Higher scores indicate higher levels of facial filter use. Internal reliability was adequate for both the appearance-enhancing and goofy versions of this scale (Appearance-enhancing: McDonald's ω $=.80$, Cronbach's $\alpha = .80$; Goofy: McDonald's $\omega = .86$, Cronbach's $\alpha =$ $.86$). This scale is available to review in supplemental materials.

2.2.2. *TikTok use*

Overall use of TikTok was assessed as a descriptive measure to characterize the sample. Participants were asked to provide their self-perceived daily hourly use of TikTok by indicating the number of hours per day they use TikTok from 1 (*less than an hour*) to 7 (*6 + hours*). Past research assessing frequency of TikTok use has used similar methods of self-report usage estimation (Vaterlaus & Winter, 2021). Participants were also asked to provide the specific number of hours spent daily on TikTok as calculated by their phone in order to obtain more accurate estimates. Participants were provided with the necessary instructions to access this information for both iPhones and Androids and asked to report their use to the nearest hour based on their actual daily usage.

2.2.3. *Body image concern*

Participants completed the Body Image Concern Inventory (BICI), a 19-item survey that measures participants' overall concern and preoccupation with different aspects of their appearance (i.e., "I spend a significant amount of time checking my appearance in the mirror" or "I have missed social activities because of my appearance;" Littleton et al., 2005). Items are rated on a five-point Likert scale, ranging from 1 (*Never*) to 5 (*Always*). Scores from all items are summed, with scores of 72 or higher indicating clinically significant body image concerns, such as those present in an eating disorder or body dysmorphic disorder (Littleton et al., 2005). This scale was developed and validated using a sample of university students, which is the same population under investigation in the present work (Littleton et al., 2005). Internal consistency in the current sample was high (McDonald's $\omega = .96$; Cronbach's $\alpha = .96$).

2.2.4. *Facial dissatisfaction*

Facial dissatisfaction was measured by the Facial Dissatisfaction Scale (FDS). This is an author-developed scale, as the research team deemed there to not be an adequate existing scale to comprehensively measure dissatisfaction with facial features. This scale was inspired by the Body Dissatisfaction Scale (Tariq & Ijaz, 2015), and the measure is comprised of 19 items assessing dissatisfaction with different facial features as originally designed. Responses are rated on a 5-point Likert scale ranging from 0 (*Never*) to 4 (*Always*). Several questions begin with the stem "I dislike the shape/size of my," and assess dissatisfaction related to a person's eyes, nose, lips, chin, jaw, and other related facial features. Three additional items asking participants if they "hate" rather than "dislike" aspects of their facial appearance were included as screeners for potentially more severe pathology. Exploratory factor analysis supported both a single-factor, 19-item version of this scale and a 2-factor, 8-item version. The present study used the briefer 2-factor version of the scale, in which the two subscales include face-related dissatisfaction (five items) and skin/hair dissatisfaction (three items). Scores on each of the subscales were averaged, with higher scores indicating higher levels of face-related dissatisfaction and skin/hair dissatisfaction, respectively. Both scales demonstrated adequate internal consistency (factor 1: McDonald's $\omega = .79$, Cronbach's $\alpha = .79$; factor 2: McDonald's $\omega = .72$, Cronbach's $\alpha = .71$). A second version includes all 19 items in a single factor, measuring overall facial dissatisfaction for which an overall score is computed by summing the scores for all 19-items. More information on the two versions of this scale is provided in the Results section, and both scales are available to review in the supplemental materials.

2.2.5. *Socio-demographics*

Participants were asked to provide their age, sex assigned at birth, gender identity, sexual orientation, race, ethnicity, and perceived weight status.

2.3. *Statistical analyses*

Jamovi (version 2.3) was utilized for data cleaning and all statistical analyses, including descriptive statistics, linear regressions, and exploratory factor analyses, as well as assessing statistical assumptions underlying the linear regressions (The Jamovi Project, 2023). To examine the constructs of both TikTok facial filter use and facial dissatisfaction, exploratory factor analyses (EFA), using principal axis factoring and promax rotation, were conducted on both the TFUS and the FDS. RMSEA and TLI values were examined to measure if the models fit descriptively, and parallel analyses were used to determine the number of factors to retain. Cronbach's alpha and McDonald's omega reliability tests were performed to test the internal consistency of the BICI, TFUS, and the FDS. Missing data points were also analyzed to determine if data was missing completely at random (MCAR). The variables included in these analyses contained less than 1 % missing data

for the current sample. Little's MCAR test showed that there was no systematic bias in missing values as well ($\chi^2[861] = 865.087, p = .454$). Given the data missing completely at random, pairwise deletion was used for all analyses.

Linear regressions were conducted to examine the associations between appearance-improving filter use and goofy filter use on both body image concern and facial dissatisfaction. Based on previously mentioned literature, it is likely that women may be more likely to use filters and to have body image concerns than men. Due to this, linear regression models were examined with gender included as covariate. Regression models were conducted on each outcome. Regression models with appearance-improving filter use as the main predictor each had three steps: (1) Step 1 included only gender, (2) Step 2 added appearance-improving filter use, (3) and Step 3 added goofy filter use. Models with goofy filter use as the main predictor each had two steps: (1) Step 1 included gender, and (2) Step 2 added goofy filter use. The assumption of linearity was met in all regressions based on examination of scatterplots. To test for homoscedasticity, a residuals-predicted plot was generated to ensure this assumption had not been violated. After examination, the assumption of homoscedasticity was found to not be violated. To test for normality of the residuals, normal probability plots were generated and examined for each regression. Normality was met in each test. Partial eta squared values were calculated as a measure of effect size. Values of .01,.06, and,14 suggest small, medium, and large effects, respectively. P-values less than .05 were deemed statistically significant.

3. Results

3.1. Descriptive statistics

Of the 339 participants who completed the full BICI, 61 participants (18 %) met or surpassed the cut score of 72 for probable BDD or ED. Participant scores on the BICI ranged from 19 to 95, with a mean score of 52.4 ($SD = 18.2$). Mean scores for appearance-improving filter use and goofy filter use subscales of the TFUS were 2.17 ($SD = 1.08$) and 2.12 ($SD = 1.05$), respectively. Mean scores for the face-related and skin/hair dissatisfaction subscales of the FDS were 1.15 ($SD = .89$) and 1.34 ($SD = .986$), respectively. The mean FDS total score was 20.2 ($SD = 14.0$). Participants mean scores for average daily TikTok use were 3.68 h ($SD = 1.88$) for perceived use and 3.61 h (SD = 3.75) for actual daily use. Descriptive statistics and correlations between variables can be found in Table 2 and 3.

3.2. Exploratory factor analyses

3.2.1. TikTok filter use scale

An EFA using promax rotation was conducted to explore the dimensionality of the six-item filter use scale. The variance accounted for by the solution, the variance accounted for by each individual factor, and the interpretability of the factors were all evaluated to determine the initial plausibility of the factor structure. To further confirm the factor structure, a parallel analysis was used. EFA of the instrument suggested that a two-factor solution best explained the data (Table 4). The variance explained by the solution was 55.2 %, and the two factors individually accounted for 29.3 % and 25.9 % of the variance, respectively. In addition, the parallel analysis indicated that a two-factor solution best represented the data when eigenvalues from the target data set were compared to eigenvalues from randomly generated data: (a) Factor 1: 3.121 vs. 0.204, and (b) Factor 2: 0.333 vs. 0.113. Using the pattern matrix for interpretation, two observed variables loaded on the first Factor (absolute values ranged from 0.713 to 0.848) and two observed variables loaded on the second Factor (absolute values ranged from 0.664 to 0.807). Items 1 and 2 loaded on third possible factor, however, due to no theoretical backing to support this third structure, the two items were consequently removed from the resulting factor structure. Factor 1 represents appearance-improving filter use, and Factor 2 represents goofy filter use. The correlation between these factors was .50. Correlations between these items were also examined to further support these 2-item subscales. Items 3 and 5 were significantly positively correlated ($r = .73, p < .001$), as were items 4 and 6 ($r = .76, p < .001$; Table 5).

3.2.2. Facial dissatisfaction scale

An EFA using promax rotation was conducted to explore the dimensionality of the 19-item facial dissatisfaction scale. The variance accounted for by the solution, the variance accounted for by each individual factor, and the interpretability of the factors were all evaluated to determine the initial plausibility of the factor structure. To further confirm the factor structure, a parallel analysis was used. EFA of the instrument suggested that a two-factor, eight-item solution best explained the data (Table 6). The variance explained by the solution was 45.8 %, and the two factors individually accounted for 26.9 % and 18.9 % of the variance, respectively. Initially, parallel analysis originally supported a five-factor structure; however, several items cross-loaded across factors. To avoid high cross-loadings, the scale was reduced from 19 items to eight items in two factors. A parallel analysis of the eight items indicated that a two-factor solution best represented the data when eigenvalues from the target data set were compared to eigenvalues from randomly generated data: (a) Factor 1: 3.09 vs. .264 and (b) Factor 2: .365 vs. .169. Using the pattern matrix for interpretation, five observed variables loaded on the first Factor (absolute values ranged from .533 to .779), and three observed variables loaded on the second Factor (absolute values ranged from .467 to .877). Factor 1 represents face-related dissatisfaction, and Factor 2 represents skin and hair dissatisfaction. The correlations between these factors was= 0.69. EFA of the instrument also suggested the possibility of a single factor solution, discussed in more detail in the online supplemental materials (See Table 9 for EFA results and Tables 10–11 for regression analyses using this version of the instrument).

3.3. Primary analyses

3.3.1. Appearance-improving filter use and body image concern

A linear regression was performed to assess the association between appearance-improving TikTok filter use and total body image concern. One model with three steps was examined. The overall model in Step 1 with gender as the predictor was statistically significant ($F[1,326] = 29.20$, $R^2 = .08$, $p < .001$), demonstrating a significant association between gender and body image concern. Participants who identified as women reported significantly greater body image concern ($\beta = .77$, $p < .001$) than men. Appearance-enhancing filter use was added as a predictor in Step 2, which resulted in significantly better model fit ($\Delta F[1,325] = 55.09$, $\Delta R^2 = .13, p < .001$). With the addition of appearance-enhancing filter use, gender remained statistically significant ($\beta = .52$, $p < .001$). Appearance-improving filter use was also significantly

Table 2
Sample characteristics – Descriptives.

	Mean	Standard Deviation	Minimum	Maximum
Age	20.3	2.70	18.00	41.00
Perceived TikTok Use	3.68	1.88	1.00	7.00
Actual TikTok Use	3.61	3.75	0.00	17.00
FDS Total	20.2	14.00	0.00	72.00
BICI Total	52.3	18.20	19.00	95.00
Appearance-Improving Filter Use	2.17	1.08	1.00	5.00
Goofy Filter Use	2.12	1.05	1.00	5.00
Skin/Hair Dissatisfaction	1.34	.99	0.00	4.00
Face-Related Dissatisfaction	1.15	.89	0.00	3.60

Note: Values for Perceived TikTok Use and Actual TikTok Use refer to hours.

Table 3
Intercorrelations of variables.

	Appearance-Improving Filter Use	Goofy Filter Use	Skin and Hair	Face	BICI	FDS Total	Gender
Appearance-Improving Filter Use	—						
Goofy Filter Use	0.67***	—					
Skin and Hair	0.29***	0.22***	—				
Face	0.35***	0.28***	0.56***	—			
BICI	0.42***	0.32***	0.58***	0.63***	—		
FDS Total	0.37***	0.26***	0.79***	0.88***	0.74***	—	
Gender	0.26***	0.22***	0.28***	0.24***	0.28***	0.28***	—

Note: Skin and Hair represents subscale of Facial Dissatisfaction Scale (FDS) measuring skin and hair dissatisfaction; Face represents subscale of FDS measuring facial feature dissatisfaction; BICI: Body Image Concern Inventory; For Gender, Man was coded as 1 and Woman was coded as 2; *** indicate $p < .001$.

Table 4
Exploratory Factor Analysis of TikTok Filter Use Scale.

Factor Loadings	Factor			
	1	2	3	Uniqueness
TFUS_1		0.38	0.66	0.35
TFUS_2	0.37		0.73	0.29
TFUS_3		0.80		0.19
TFUS_4	0.71			0.31
TFUS_5		0.66		0.31
TFUS_6	0.85			0.16

Note. TFUS: TikTok Filter Use Scale; 'Principal axis factoring' extraction method was used in combination with a 'promax' rotation.

Table 5
Correlation matrix of TikTok Filter Use Scale items.

Correlation Matrix	TFUS_3	TFUS_4	TFUS_5	TFUS_6
TFUS_3	—			
TFUS_4	0.63***	—		
TFUS_5	0.73***	0.51***	—	
TFUS_6	0.52***	0.76***	0.67***	—

Note: TFUS: TikTok Filter Use Scale; ***indicate $p < .001$

Table 6
Exploratory factor analysis of facial dissatisfaction scale – 2-Factor Version.

Factor Loadings	Factor		
	1	2	Uniqueness
FDS_3	0.78		0.53
FDS_15	0.65		0.42
FDS_4	0.63		0.63
FDS_2	0.59		0.53
FDS_1	0.53		0.66
FDS_12		0.87	0.36
FDS_11		0.63	0.60
FDS_13		0.47	0.62

Note. FDS: Facial Dissatisfaction Scale; 'Principal axis factoring' extraction method was used in combination with a 'promax' rotation.

positively associated with body image concern, as participants who reported higher use of appearance-improving TikTok filters also reported higher levels of body image concern ($\beta = .38$, $p < .001$). Goofy filter use was added as a predictor in Step 3. The change in model fit from Step 2 to Step 3 was not significant ($\Delta F[1,324] = .48$, $\Delta R^2 = .00$, $p = .490$). While gender ($\beta = .52$, $p < .001$) and appearance-improving filter use ($\beta = .34$, $p < .001$) remained statistically significant with the addition of goofy filter use, goofy filter use was not significantly associated with body image concern within the Step 3 model ($\beta = .05$, $p = .49$; Table 7).

3.3.2. *Goofy filter use and body image concern*

The association between goofy TikTok filter use and body image concern was also assessed through a linear regression. One model with two steps was examined. The first step included gender as a predictor, and results indicated a significant association between gender and body image concern ($F[1,328] = 29.10$, $R^2 = .08$, $p < .001$). Participants who identified as women reported significantly higher levels of body image concern ($\beta = .76$, $p < .001$) than men. Goofy filter use was added as a predictor in Step 2, resulting in a significant change in model fit from Step 1 to Step 2 ($\Delta F[1,327] = 27.40$, $\Delta R^2 = .071$, $p < .001$). Gender remained statistically significant in the Step 2 model ($\beta = .61$, $p < .001$), and goofy filter use was also significantly positively associated with body image concern. Participants who reported higher usage of goofy filters also reported higher levels of body image concern ($\beta = .27$, $p < .001$; Table 8).

3.3.3. *Appearance-improving filter use and facial dissatisfaction*

The association between appearance-improving TikTok filter use and face-related dissatisfaction was also assessed via linear regression. One model with three steps was examined. The Step 1 model with gender as the sole predictor was significant, ($F[1,329] = 21.30$, $R^2 = .06$, $p < .001$), finding a significant association between gender and face-related dissatisfaction. Participants who identified as women reported significantly greater face-related dissatisfaction ($\beta = .65$, $p < .001$) compared to men. The addition of appearance-improving filter use in Step 2 resulted in significantly better model fit ($\Delta F\,[1,328] = 35.92$, $\Delta R^2 = .09$, $p < .001$). With this addition, gender remained statistically significant as a predictor ($\beta = .44$, $p = .002$). Appearance-improving filter use was also significantly positively associated with face-related dissatisfaction. Participants who reported higher usage of appearance-improving filters also reported higher levels of face-related dissatisfaction ($\beta = .32$, $p < .001$). Goofy filter use was added as a predictor in Step 3, but did not result in a significant change in model fit ($\Delta F[1,327] = .75$, $R^2 = .00$, $p = .39$). In the Step 3 model, both gender ($\beta = .43$, $p = .002$) and appearance-improving filter use ($\beta = .28$, $p < .001$) remained statistically significant; however, goofy filter use was not significant when included in a model with appearance-improving filter use ($\beta = .06$, $p = .39$; Table 7).

Next, a linear regression with three steps was performed to assess the association between appearance-improving TikTok filter use and skin/hair dissatisfaction. Again, Step 1 included gender as the sole predictor, and the Step 1 model was significant ($F[1,331] = 29.10$, $R^2 = .08$, $p < .001$). There was a significant association between gender and skin/hair dissatisfaction such that women reported greater skin/hair dissatisfaction ($\beta = .74$, $p < .001$) than men. Appearance-improving filter use was added as a predictor in Step 2, resulting in a significant change in model fit compared to Step 1 ($\Delta F[1,330] = 19.16$, $\Delta R^2 = .05$, $p < .001$). Gender remained a significant predictor ($\beta = .59$, $p < .001$) in the Step 2 model. Appearance-improving filter use was also significantly associated with skin/hair dissatisfaction in the Step 2 model, with participants

Table 7
Appearance-improving filter use regression coefficients.

Dependent Variable	Predictor	B	Std. Error	β	η_p^2	p	R^2	F	ΔR^2	ΔF
BICI	Step 3						.22	29.80***	.00	.48
	Gender	9.36	2.46	.52	.04	<.001				
	Appearance-Improving Filter Use	5.83	1.16	.34	.07	<.001				
	Goofy Filter Use	.82	1.17	.05	.00	.49				
FDS (Face)	Step 3						.16	20.10***	.00	.75
	Gender	.38	.12	.43	.03	.002				
	Appearance-Improving Filter Use	.23	.06	.28	.05	<.001				
	Goofy Filter Use	.05	.06	.06	.00	.39				
FDS (Skin/Hair)	Step 3						.13	16.60***	<.001	.05
	Gender	.58	.14	.58	.05	<.001				
	Appearance-Improving Filter Use	.20	.06	.22	.03	.002				
	Goofy Filter Use	.02	.07	.02	<.001	.82				

Note: ***indicate p < .001.

Table 8
Goofy Filter use regression coefficients.

Dependent Variable	Predictor	B	Std. Error	β	η_p^2	p	R^2	F	ΔR^2	ΔF
BICI	Step 2						.15	29.40***	.07***	27.40***
	Gender	11.10	2.53	.61	.06	<.001				
	Goofy Filter Use	4.72	.90	.27	.08	<.001				
FDS (Face)	Step 2						.11	21.30***	.05***	20.00***
	Gender	.46	.12	.51	.04	<.001				
	Goofy Filter Use	.20	.04	.24	.06	<.001				
FDS (Skin/Hair)	Step 2						.10	19.3***	.03***	9.34***
	Gender	.64	.14	.64	.06	<.001				
	Goofy Filter Use	.15	.05	.16	.03	.002				

Note: ***indicate p < .001.

who reported higher appearance-improving filter use also reporting higher levels of skin/hair dissatisfaction (β = .23, $p < .001$). Finally, goofy filter use was added as a predictor in Step 3. Again, the addition of goofy filter use as a predictor did not result in significantly better model fit (ΔF[1,329] = .05, ΔR^2 <.001, p = .82). In the Step 3 model, both gender (β = .58, $p < .001$) and appearance-improving filter use (β = .22, p = .002) remained statistically significant. However, goofy filter use was not significant when included in a model with appearance-improving filter use (β = .02, p = .816; Table 7).

3.3.4. *Goofy filter use and facial dissatisfaction*

The association between goofy TikTok filter use and face-related dissatisfaction was assessed using a linear regression with two steps. The Step 1 model indicated a significant association between gender and face-related dissatisfaction (F[1,331] = 21.40, R^2 = .06, $p < .001$). Participants who identified as women reported significantly higher levels of face-related dissatisfaction (β = .65, $p < .001$) than men. Goofy filter use was added as a predictor in Step 2, resulting in a significant change in model fit (ΔF[1,330] = 20.00, ΔR^2 = .05, $p < .001$).With the addition of goofy filter use, gender remained a significant predictor (β = .51, $p < .001$). Goofy filter use was also significantly associated with face-related dissatisfaction, as participants who reported higher use of goofy filters also reported higher levels of face-related dissatisfaction (β = .24, $p < .001$; Table 8).

A final linear regression with two steps was performed to assess the association between goofy TikTok filter use and skin/hair dissatisfaction. The Step 1 model with gender as the predictor was significant, (F [1,333] = 28.60, R^2 = .08, $p < .001$), finding a significant association between gender and skin/hair dissatisfaction. Women reported significantly higher levels of skin/hair dissatisfaction (β = .74, $p < .001$) than men. Goofy filter use was added as a predictor in Step 2, resulting in a significant change in model fit, (ΔF[1,332] = 9.34, ΔR^2 = .03, p = .002). With the inclusion of goofy filter use, gender remained a significant predictor (β = .64, $p < .001$). Goofy filter use was also significantly associated with skin/hair dissatisfaction, with participants who reported higher goofy filter use also reporting significantly greater skin/hair dissatisfaction (β = .16, p = .002; Table 8).

4. Discussion

While previous studies have examined other appearance-focused online behaviors and their associations to body image outcomes, this study is the first to the authors' knowledge to examine how facial filter use is associated with body image concern and facial dissatisfaction on TikTok. Burnell et al. (2022) found associations to other body image constructs (namely, appearance preoccupation) when examining filters on another social media platform (Snapchat), and the current study was able to extend these findings to body image concern and facial dissatisfaction. Filter use, when examined independently of each type of intentional use, was positively associated with all measured body image outcomes. When included in the same model, only appearance-improving filter use was associated with these outcomes.

4.1. *Exploratory factor analyses*

Given the current study used author-developed measures, the factor structure of both the TFUS and the FDS were examined. The TFUS loaded onto 2-factors: (1) appearance-improving filter use and (2) goofy filter use. The items loaded as expected, with items referencing appearance-improving intentions loading onto one factor and those

mentioning goofy intentions loading onto the other. However, items 1 and 2 loaded on a third unnamed factor. While this was unexpected, a possible rationale for these findings exists in that these two items referenced posting a video on TikTok rather than simply using the filter. It may be that those who use facial filters do not often post these videos to the platform, instead using them for their own private enjoyment. Items 1 and 2 were thus removed from the scale given there was no theoretical reason to support their inclusion, as they target different intentions in filter use than the other items. However, it may be worthy for future researchers who choose to use this scale to test the factor structure again to examine if this third factor remains present. As the TFUS is relatively short, the creation of additional items targeting usage behaviors when using TikTok facial filters may also be helpful to further strengthen the scale's ability to measure facial filter usage.

The factor structure of the FDS was also examined in the current study, and two possible factor structures were deemed to fit well. The first possible version of the FDS that included two factors assessing both face-related dissatisfaction and skin/hair dissatisfaction was comprised of items assessing more general forms of facial appearance (i.e., eyes, nose, lips, chin, symmetry, skin texture, skin tone, and hair). The original scale, however, included items assessing other aspects of the face which were not supported, perhaps due to the level of specificity in facial appearance that they measure as opposed to more general aspects of appearance (the spacing between the eyes vs. general shape of features). EFA also supported a single-factor version of the FDS. The statistical support for this structure was lower than the two-factor structure; however, this version may be more useful in some contexts requiring a more comprehensive view of facial dissatisfaction facial image disturbance as compared to dissatisfaction with specific components of the face. Future studies should examine both of these factor structures of the FDS to examine which versions may be appropriate different populations.

4.2. Filter use and body image outcomes

The first hypothesis, that higher levels of appearance-improving filter use would be associated with higher levels of body image concern, was supported in the current study with a large effect size. This is in line with previous research which finds social media usage, and filter use specifically, to be associated with higher levels of body image concern (Cohen et al., 2017; Fardouly & Vartanian, 2016; Holland & Tiggemann, 2016). While there are several theories that may begin to explain this association, such as social comparison theory and the tripartite influence model, it is difficult to fully understand due to the complex way that facial filters may interact with body image concerns. While one perspective is that the frequent use of filters could exacerbate body image concerns over time, it could also be argued that facial filters provide adaptive aspects in the short term. Having these filters to return to when experiencing appearance-related distress may temporarily reduce anxieties in those with body image concerns, as they are able to view their appearance in a more desired form. Inversely, frequently having access to a filtered version of their appearance may lead to greater feelings of distress when viewing their appearance in unaltered reflections, particularly if they do not resonate with or recognize their "real" appearance as their own.

The second hypothesis, which posited that participants reporting higher appearance-improving filter use would also report higher levels of facial dissatisfaction, was also supported with medium-to-large effects that remained constant across all versions of the FDS. This finding is partially in line with previous research. In a study testing the effects of beautifying vs. uglifying filter use, Dijkslag et al. (2024) found beautifying filter usage to decrease body satisfaction. However, Burnell et al. (2022) did not find any significant association between Snapchat lens use and facial satisfaction despite finding higher levels of Snapchat lens use and higher levels of body surveillance and beauty-ideal internalization. Burnell et al. (2022) used a subscale from the Body Parts Satisfaction Scale (BPSS; Berscheid et al., 1973) to measure facial satisfaction, which may explain why their findings diverged from those of the current study (which assessed facial *dissatisfaction*). The BPSS subscale asks participants to express their degree of satisfaction or dissatisfaction on several aspects of the face (eyes, nose, etc.,) on a six-point scale from extremely satisfied to extremely dissatisfied, while the FDS asks respondents to report the frequency with which they are dissatisfied with certain facial features ranging from never to always. Given the FDS exclusively measures dissatisfaction, it may have more gradation in assessing the severity of dissatisfaction compared to the BPSS. Future researchers should further examine filter use and facial (dis)satisfaction to establish more consistent findings.

The current study also found medium, positive bivariate associations between goofy TikTok filter use and body image concern and goofy TikTok filter use and facial dissatisfaction, with those reporting greater goofy filter usage also reporting greater body image concerns and facial dissatisfaction. While there is no previous literature to directly support these associations, these findings may still be in line with past research which finds an association between the use of appearance focused social media and poorer body image outcomes (Cohen et al., 2017). While goofy filters are not necessarily appearance-improving, they are still a key feature of appearance-focused social media. For example, Burnell et al. (2022), found a significant association between the number of photos taken and body image outcomes, specifically that those who took more photos to find a "suitable" option also had greater body image concerns than those who took fewer photos, suggesting that it may not be the type of filter that is associated with body image, but rather the act of using filters in general. Similar findings connecting selfies and poorer body image outcomes were found by Cohen et al. (2018). When both appearance-improving filter use and goofy filter use were included in the same model in the present study, goofy filter use was no longer found to be associated with body image concerns or facial dissatisfaction. While filter use in general may be associated with body image concerns, it may be that appearance-improving filter use has a stronger association with body image concerns and facial dissatisfaction than goofy filter use, thereby partially providing support that goofy filter use is associated with body image concerns and facial dissatisfaction.

4.3. Implications

The current study's findings connecting facial filter use with body image concerns may have several clinical implications. These findings highlight the salience of social media use, particularly usage of facial filters to body image concerns. As stated in the tripartite influence model, media may be a salient form of psychosocial pressure that influences the internalization of body ideals, ultimately leading to disordered eating (Thompson et al., 1999). Additionally, the cognitive behavioral model of BDD (Veale, 2004) suggests that individuals with BDD may seek out reflective objects, such as mirrors, to reduce anxiety around their appearance and compare their real-life appearance to idealized versions of their appearance, which can be readily replicated by facial filters. Given that the current study found an association between filter use and body image concerns, this new type of behavior may be relevant to clinicians when treating patients with BDD and /or eating

disorders. If an individual consistently views their appearance with these filters, it can be helpful for clinicians to be aware of this behavior in order to address filter use during treatment.

These findings may have additional implications for social media companies and users hoping to minimize the negative psychological impacts of social media use. While platforms such as TikTok have made changes to their policies relating to the removal of content promoting disordered eating, it is more difficult to intervene in the context of facial filters (TikTok, 2019). Some may suggest including warning labels identifying the potential harm facial filters may have on body image outcomes as an intervention; however, past research has shown these labels are ineffective in reducing poor body image when paired with appearance-focused content and may even worsen body image (Danthinne et al., 2020). While removing facial filters entirely remains an option, considerable research is needed before such an extreme undertaking is recommended.

4.4. Limitations and future directions

The current study is not without limitations. As the entire recruited sample consisted of university students, results may not directly translate to other populations who experience body image concern and facial dissatisfaction. It is also worth noting that the current sample has a much higher prevalence of possible BDD (18 %) than those in the general population (2.4 %; Koran et al., 2008) and among young adults (3.4 %; Möllman et al., 2017). While the current study's findings were largely consistent with past work in similar areas, it could be reasoned that the higher prevalence of BDD in the current sample may also limit the generalizability of this study's findings. Of note, in addition to being university students, the current sample was predominately female and users of TikTok, so findings may be mostly generalizable to this population rather than the population at large. Future researchers should examine these same constructs in samples with a lower prevalence rate of BDD to ensure that these findings remain consistent. Additionally, the current sample reported an average TikTok use of 3.61 hours per day, which is much higher than other studies reporting daily use. Other studies have found college students to report TikTok usage of around one hour per day (Rogowska & Cincio, 2024; Vaterlaus & Winter, 2021). Vaterlaus and Winter (2021) found that participants reported using the app for an average of 63 minutes a day. Inclusion criteria for the Vaterlaus and Winter study specified that participants must either currently use or have previously used TikTok and asked them to report average daily TikTok use. In the current study, however, participants were required to have used TikTok in the two weeks prior to participation. These different criteria may partially explain differences in average use, as past users may not accurately remember how long they would spend on the app per day. One study conducted by a consumer-facing company suggested that 47 % of college students sampled reported TikTok usage between 3 and 5 hours per day, but exact methodology for this survey was unclear (Intelligent.com, 2024). The higher levels of daily TikTok reported in the current sample may impact the generalizability of these findings may to the general population, which may use TikTok to a lesser extent.

Another limitation is the use of the author-developed scales to measure TikTok use and facial dissatisfaction. Given the paucity of literature on filter use, it was necessary to create a scale assessing filter use on TikTok. Accordingly, this scale has not been validated outside of the current study. While the EFA conducted as part of the present work supported a two-factor construct characterized by two separate filter use intentions (appearance improvement and goofiness), future studies that should further investigate the validity and factor structure of this scale in other populations. This same limitation pertains to the creation and use of the Facial Dissatisfaction Scale. For this scale, EFA provided two adequate factor structures, emphasizing the need for further testing and refinement of the scale to determine the appropriateness of each version in different populations of study types. Despite the limitations of the FDS and the TFUS, it is our hope that the development and use of these scales will help future researchers bridge gaps in research relating to facial dissatisfaction and facial filter use.

Finally, it is also worth noting that the current study is cross-sectional, and these findings are correlational in nature. While associations between these constructs were found, the temporal ordering of these associations has yet to be established. It is possible that those with pre-existing body image concerns use facial filters with higher frequency to alleviate negative thoughts about their appearance. However, it is equally possible that using these filters may increase body image concerns in the long-term, as they may drive discrepancies between a person's 'real' and 'perceived' appearances. Future researchers may also want to examine filter use and its association to body image longitudinally to better identify the temporal order of these constructs. Regardless of specific methodology, moving beyond correlational and cross-sectional designs will be necessary as research into the specific uses of social media that most closely relate to and influence body image dissatisfaction and disordered eating advances.

The present study is among the first to assess the relationship between TikTok facial filter usage and body image outcomes, finding that use of both appearance-enhancing and goofy filters is significantly related to body image concerns and facial dissatisfaction when assessed independently of one another. However, when both types of filter use are included simultaneously in a model, goofy-filter is no longer significantly related to the outcomes. This study also introduces and provides initial psychometric investigation into two new measures, the TFUS and the FDS. Given TikTok is one of the fastest growing and most commonly used social media applications (Pew Research Center, 2024), it is crucial to investigate components of the app that may relate to body image outcomes to better understand the risks faced by users.

CRediT authorship contribution statement

Nicolas S. Caravelli: Writing – review & editing, Writing – original draft, Resources, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Haley A. Henriksen:** Writing – review & editing, Writing – original draft, Project administration. **Aaron J. Blashill:** Writing – review & editing, Supervision, Resources, Methodology, Investigation, Conceptualization.

Conflict of interest

The authorship team confirms that we have no known conflicts of interest associated with this publication and that there has been no significant financial support for this work that could have impacted its outcome. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Appendix A. TikTok Facial Filter Use Scale

How often have you engaged in the following behaviors on TikTok over the last 2 weeks? (1-*Never*, 2-*Rarely*, 3-*Sometimes*, 4-*Often*, 5-*Always*)

1. Upload a TikTok with a filter to make myself look more attractive.
2. Upload a TikTok with a filter to make myself look goofy.
3. Search for and apply a filter to see if it makes myself look more attractive.
4. Search for and apply a filter to see if it makes myself look goofy.
5. See if I look more attractive with a filter I saw on my For You Page.
6. See if I look goofy with a filter I saw on my For You Page.

Appendix B. Facial Dissatisfaction Scale

Please respond to these items with how often you have experienced dissatisfaction with aspects of your facial appearance within the last two weeks. 1 (*Never*) to 5 (*Always*)

1. I dislike the shape/size of my eyes.
2. I dislike the shape/size of my lips.
3. I dislike the shape/size of my nose.
4. I dislike the shape/size of my chin.
5. I dislike the structure of my jaw.
6. I dislike the color of my eyes.
7. I think my eyes are too far apart/too close together.
8. I dislike the size of my forehead.
9. I dislike the size of my cheeks.
10. I dislike how wide my face is.
11. I dislike the texture of the skin on my face.
12. I dislike the tone of the skin on my face.
13. I am dissatisfied with my hair.
14. I dislike the color of my hair.
15. I am dissatisfied with the symmetry of my face.
16. I am dissatisfied with the whiteness of my teeth.
17. I hate certain features on my face.
18. I hate my face.
19. I am disgusted by my face.

Appendix C. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.bodyim.2025.101877.

Data availability

The authors do not have permission to share data.

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Association between beauty standards shaped by social media and body dysmorphia among Egyptian medical students

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This study examines the relationship between exposure to unattainable beauty standards via social media and the prevalence of Body Dysmorphic Disorder among medical students in Egypt. The rapid development of digital platforms, particularly social media, has brought about a wider dissemination of unattainable beauty standards that may contribute to body image disorders and psychological problems. Given the unique pressures faced by medical students, who represent both consumers and influencers in health-related content, the current study attempts to ascertain whether excessive engagement with distorted beauty portrayals correlates with higher rates of BDD symptoms in this population. This was a cross-sectional questionnaire-based study consisting of 1126 undergraduate medical students, with a mean age of 20.8 years enrolled in any Egyptian medical school registered in the academic year 2023–2024, specifically from August–October 2024, except non-medical, graduate, and non-Egyptian students who met the exclusion criteria. We privately gathered answers via colleagues and electronically via online Google forms posted on social media groups. To our knowledge, this is the first study to investigate the relationship between social media use and BDD among medical students. According to social media practices, WhatsApp, Facebook, Instagram, YouTube, and TikTok were mostly used for 4–7 h daily. Most rarely or sometimes, take selfies, edit them with filters, and share them with others. The summary of BDDQ answers demonstrated that 6.3% of Egyptian medical students enrolled met the criteria for BDD. The majority reported that they do not like their face, and this leads to suffering from bullying in school or work, resulting in avoiding certain clothes as an avoidance behavior. The majority reported engaging in positive self-talk, participating in offline activities or hobbies, and unfollowing accounts promoting unattainable beauty standards as a coping strategy against unattainable beauty standards shaped by social media. Our study found that BDD is highly prevalent among social media users, especially on text-based platforms. The prevalence of BDD among Egyptian medical students is 6.3%, which is higher than worldwide. Interestingly, Egyptian medical students enrolled in our study believe that promoting body positivity, educating users about the risks of body dysmorphia, restricting content that promotes unrealistic body standards, and providing resources and support for those affected, respectively, are the critical measures that social media platforms should take to address body dysmorphia.

Keywords Body dysmorphia, Social media, Unattainable beauty, Medical students

Body image refers to how an individual perceives, thinks about, and feels about their body. It encompasses how one visually represents their body, such as in a mirror reflection, and is influenced by societal constructs shaped by cultural and societal standards. This understanding is formed through body ideals heavily propagated by media, family, and peers[1]. Media platforms have had a major impact on Body image, as there is strong evidence suggesting the negative effects of objectifying beauty standards presented on mass media such as TV and Magazines[2]. For the past 2 decades, social media has replaced traditional media as the main outlet for

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communication and sharing cultural norms that influence today's beauty standards. Facebook is considered the main priority social media app in Egypt, with 56 million active users and its greatest user demographic ranging from 18 to 44 years of age[3]. But how does social media affect body image? Social media allows individuals to upload idealized versions of themselves on their accounts; these images are often exaggerated with the use of filters and edits. Repeated exposure to these images leads to an increase in social comparison and internalization of these beauty ideals and thus leads to worsening dissatisfaction with body image. Body dissatisfaction has unfortunately been linked to psychological stress, which can result in a variety of psychological disorders, such as body dysmorphic disorder (BDD) and anorexia nervosa[4].

BDD is an under-recognized but relatively common psychiatric disorder with a worldwide prevalence of 1.7 to 2.4%. A recent study conducted in Saudi Arabia has concluded that almost 9.5% of the patients visiting the dermatology clinic have BDD, which shows that there is an alarming lack of awareness about this disorder[5]. DSM V has categorized BDD as a disorder associated with a constant preoccupation of an individual's perceived visual look, with repetitive behaviors aimed at hiding or fixing any possible flaws, although these flaws may be unobserved or minimally visible to others. Such behaviors must have a significant toll on the daily activities and social life of the patient and must not be associated with any other psychiatric disorder, i.e., eating disorders (Anorexia Nervosa, Bulimia Nervosa)[6]. According to various studies, BDD is most common in adolescents ranging between 13 and 18 years of age, and according to the CAPMAS (Central Agency for Public Mobilization and Statistics), the percentage of youth in EGYPT in 2021 statistics is 21 million, which forms about 21% of the population. Thus, this makes Egypt a significant breeding ground for individuals with BDD[7]. There has been no study discussing the association between BDD and social media usage among Egyptian medical students, the attitude that should be adopted to deal with its symptoms, and the role of social media platforms in amplifying its effects on their mental health. Thus, this study was conducted to evaluate the prevalence of body dysmorphic disorder (BDD) symptoms among Egyptian medical students, and the association between social media usage, and body dysmorphia.

Methods and materials

Study design and participants

This questionnaire-based cross-sectional study was conducted in Egypt. The study population targeted Egyptian medical students during August–October 2024. The participants were Egyptians of both genders, active on at least one social media platform, and not diagnosed with mental disorders. Non-social media users, non-Egyptians, and those with severe mental health conditions were excluded from the study as per the exclusion criteria. We informed participants at the beginning of the questionnaire that they were excluded if they had any mental disorders. So we excluded participants who self-reported having a mental health disorder because the study aimed to isolate the impact of social media on BDD in individuals without pre-existing mental health conditions that could significantly influence body image. The sample size was calculated online (https://www.openepi.com/SampleSize/SSPropor.htm). Assuming that the estimated proportion of the general population who met the criteria of BDD from a previous study in Saudi Arabia is 24.4%, according to Ateq Khadijah. et al.[8] (p), with a 5% margin of error, and a 95% confidence interval, the minimum required sample size is 283. By adding a 40% expected drop rate, the final minimum sample size is 396. In our study, we used convenience sampling methods to recruit participants, which involved selecting medical students who were readily accessible and willing to participate. While we aimed to include students from various governorates to reflect geographic diversity, no formal weighting was applied to balance representation across regions. The survey was distributed through representatives from each governorate using an instant messaging app (What's App, Facebook, messenger Inc.) and a direct link supplied by the survey administration software (Forms, Google Inc.). To overcome potential biases, we implemented strategies such as clear communication about the survey's purpose and reminders to encourage participation. After answering all the questions, participants were instructed to send the web form to the web server. Later, the data was transmitted via the webserver to an Excel spreadsheet (version 16.0, Microsoft Corp., Albuquerque, NM, USA) for assessment.

Data collection procedure

A structured questionnaire comprising four sections: demographic information, social media usage, body dysmorphic disorder concern questionnaire, and coping mechanisms and solutions, was developed based on a review of existing literature[8,9] and was validated by a panel of experts in public health and psychiatry departments. Reliability and internal consistency were evaluated using the Cronbach alpha test. We conducted a pilot study on 32 students to test the reliability of the questionnaire. BDDQ (BDDQ) showed an accepted reliability value (Cronbach's Alpha = 0.62). The questionnaire was administered in English as medical students are well-oriented with these concepts in the questionnaire. This questionnaire was designed with four consecutive sections to evaluate the link between body dysmorphic disorder and unattainable beauty standards shaped by social media. The first section of the questionnaire inquired about age, gender, academic level, socioeconomic situation, marital status, and residence. The second portion of the questionnaire analyzed social media use and behavior using two multiple-choice questions and three 4-point Likert questions, such as "To what extent do you take selfies?" (Always, Sometimes, Rarely, or Never). In addition, the following question was used to assess social media exposure: "How much time do you usually spend on social media?" (Low exposure is defined as less than 1 h per day, average exposure is 1–3 h per day, and high exposure is 4–7 h or more). The third part was the body dysmorphia disorder questionnaire. It was composed of five close-ended questions, each had a yes or no answer. The first and second questions asked the participants whether their appearance and their thoughts about it worried and preoccupied them. A yes answer to both of them was a must. The third question assessed the level of distress and interference with social and work life that these thoughts caused. It had 4 parts, a yes answer to any was a must. The fourth question asked about the average time spent per day thinking about appearance.

Spending 1 h or more was a must to diagnose BDD. Thus, BDD was diagnosed on a total score of 4 or more. The fifth question asked about the fear of getting too fat. A yes answer to this question excluded the participants from BDD diagnosis due to the probability of confounding with eating disorders. A no-answer to question 5 was a must without an additional score. The fourth part examined coping mechanisms and solutions through two multiple choice questions and one 5-point Likert question (1 = strongly disagree; 5 = strongly agree), for example, "What strategies do you use to cope with negative feelings about your body image due to social media?" and "Would you support initiatives aimed at raising awareness about social media-related body dysmorphia?"

Statistical analysis

Data were processed with IBM-SPSS software (IBM Corp., 2020). IBM SPSS Statistics for Windows, Version 27.0 (Armonk, NY: IBM Corporation). Categorical data were described with numbers and percentages. Continuous data were described using mean and standard deviation from normality charts. The chi-square test was used to compare frequencies. For multinomial categorical variables, dummy variables were created to indicate the effect of each category using chi-square. Multivariate binary logistic regression was conducted to identify predictors of BDD. Significant results were defined as a p-value $<= 0.05$.

Results

Our sample consisted of 1126 undergraduate medical students, with a mean age of 20.8 years (1.6). 719 (63.9%) were females, and 407 (36.1%) were males. The majority were from Dakahlia, Cairo, Qena, Damietta, and Giza, 327 (29%), 282 (25%), 160 (14.2%), 82 (7.3%), and 45 (4%), respectively. The economic status of the majority, 1044 (92.7%), was middle level. The economic status was classified based on income brackets (low: < 10,000 EGP; middle: 10,000–30,000 EGP; high: > 30,000 EGP). 1114 (98.9%), we're single. 793 (70.4%) were from urban residences (Table 1).

The platforms of WhatsApp, Facebook, Instagram, YouTube, and TikTok were mostly used, 729 (64.7%), 626 (55.6%), 601 (53.4%), 485 (43.1%), and 332 (29.5%), respectively. Most participants spend 4 to 7 h and 1 to 3 h daily on social media, 563 (50%) and 374 (33.2%), respectively. The majority rarely or sometimes take selfies, 484 (43%), 454 (40.3%), sometimes or never edit selfies with filters, 348 (30.9%), 336 (29.8%), and rarely or sometimes share them with others, 446 (39.6%), 363 (32.2%), respectively (Table 2).

		Mean	SD	N	%
Age		20.8	1.6		
Sex	Male			407	36.1%
	Female			719	63.9%
Governorate	Dakahlia			327	29%
	Cairo			282	25%
	Qena			160	14.2%
	Damietta			82	7.3%
	Qalyubia			38	3.4%
	Giza			45	4%
	Sharqia			29	2.6%
	Kafr El-Sheikh			26	2.3%
	Gharbia			21	1.9%
	Port Said			19	1.7%
	Ismailia			21	1.9%
	Assuit			21	1.9%
	Beni Sweif			15	1.3%
	Alexandria			8	0.7%
	Suez			8	0.7%
	Sini			7	0.6%
	Others			17	1.5%
Economic status	High			72	6.4%
	Middle			1044	92.7%
	Low			10	0.9%
Marital Status	Single			1114	98.9%
	Married			9	0.8%
	Divorced			1	0.1%
	Widowed			2	0.2%
Location	Urban (City)			793	70.4%
	Rural (Countryside)			333	29.6%

Table 1. Characteristics of the study population.

Question	Answers	N	%
Which social media platform do you use the most?*	Facebook	626	55.6%
	Whatsapp	729	64.7%
	Instagram	601	53.4%
	Twitter	203	18.0%
	Snapchat	190	16.9%
	Tik Tok	332	29.5%
	Youtube	485	43.1%
	Linked in	35	3.1%
	Telegram	39	3.5%
	Other platforms	18	1.6%
Average time spent on social media per day	More than 7 h	167	14.8%
	4–7 h	563	50%
	1–3 h	374	33.2%
	Less than 1 h	22	2%
To what extent do you take selfies?	Always	96	8.5%
	Sometimes	454	40.3%
	Rarely	484	43%
	Never	92	8.2%
To what extent do you use filters to edit selfies?	Always	121	10.7%
	Sometimes	348	30.9%
	Rarely	321	28.5%
	Never	336	29.8%
To what extent do you share selfies with others?	Always	69	6.1%
	Sometimes	363	32.2%
	Rarely	446	39.6%
	Never	248	22%

Table 2. Social media practices. *Multiple response analysis.

Our primary outcome was to assess the prevalence of Body Dysmorphic Disorder (BDD) in medical students. Only 71 (6.3%) participants met the criteria for BDD. The summary of BDDQ answers is shown in Table 3. 621 (55.2%) were worried about their appearance. Of them, 55.9% thought about it a lot as a problem, mostly their faces (16.7%), their abdomen (9.7%), weight (6.1%), noses 51 (7.9%), thighs (4.5%), and all their body (4.3%). The appearance problem upset 36.5% of students and interfered with the social activities of 26.9%. 27.6% reported avoidance behaviors, mostly towards clothes (27.7%), socialization (20.9%), and taking and publishing photos (9.6%). 84.7% spent 1 h or more per day thinking about their appearance. 44.9% reported that their main concern was they were not thin enough or might get too fat and thus were excluded from the BDDQ scores calculation.

Our secondary outcome was to explore the effect of sociodemographics and social media practices on BDD, as shown in (Table 4). 63.4% were females with a mean age of 20.8 (1.7). The age mean differed significantly between BDD and non-BDD ($p<0.001$). We found a significant difference between BDD and non-BDD according to the Governorate ($p=0.03$), especially Dakahlia ($p=0.002$) and Qena ($p<0.001$). A significant difference was also found regarding high economic status ($p=0.03$) marriage ($p=0.05$), and residence ($p=0.03$). Multivariate logistic regression revealed the predictors of BDD as shown in Table 5. Participants from the Governorates of Dakahlia were less likely to have BDD (OR = 0.34, $p=0.003$, 95% CI 0.17–0.69). However, participants were more likely to have BDD if they were 21 years old or less (median age) (OR = 2.56, $p=0.004$, 95% CI 1.36–4.82), from Qena (OR = 2.56, $p=0.001$, 95% CI 1.48–4.43), high economic status level (OR = 2.29, $p=0.03$, 95% CI 1.09–4.81), and rural residence (OR = 1.71, $p=0.03$, 95% CI 1.04–2.79).

Participants reported the strategies they use to cope with negative feelings about their body image (Table 6). 445 (39.5%) engage in positive self-talk, 353 (31.3%) participate in offline activities or hobbies, and 343 (30.5%) unfollow accounts promoting unattainable beauty standards. Also, 331 (29.4%) limit social media usage, 269 (23.9%) seek support from friends or family, and 97 (8.6%) consult a mental health professional.

Participants suggested measures that social media should take to address body dysmorphia (Table 6). The majority suggested education about BDD risks 616 (54.7%), promotion of body positivity 536 (47.6%), and restriction of unfavorable content 510 (45.3%). They also suggested providing resources and support 484 (43%) and implementing mental health support features to 446 (39.6%). About half of participants, 550 (48.8%), strongly support initiatives aimed at raising awareness about social media-related body dysmorphia.

Discussion

Body dysmorphic disorder is a common and often severe psychological condition. Given the high prevalence of social media use and BDD in young people, the current cross-sectional study sought to contribute to the small

		N	%
1. Are you worried about how you look?	Yes	621	55.2%
	No	505	44.8%
2. If yes, Do you think your appearance problems a lot and wish you could think about them less? (N=621)	Yes	347	55.9%
	No	274	44.1%
If yes, What are the body areas that you do not like?* (N=621)	Face	104	16.7%
	Nose	49	7.9%
	Eyes	15	2.4%
	Hair	25	4%
	Teeth	24	3.9%
	Abdomen	60	9.7%
	Chest	21	3.4%
	Back	14	2.3%
	Shoulders	6	1%
	Arms	25	4%
	Hands	6	1%
	Nails	2	0.3%
	Hips	24	3.9%
	Thighs	28	4.5%
	Legs	12	1.9%
	Height	10	1.6%
	Weight	38	6.1%
	Skin	21	3.4%
	Shape	13	2.1%
	All	27	4.3%
3.			
a. Has this problem often upset you a lot?	Yes	411	36.5%
	No	715	63.5%
b. Has it often gotten in the way of doing things with friends, dating, your relationship with people, or your social activities?	Yes	303	26.9%
	No	823	73.1%
c. Has it caused you problems in School, work, or other activities?	Yes	131	11.6%
	No	995	88.4%
If yes, What are they?* (N=131)	Avoid physical activities	9	6.9%
	Bullying	26	19.8%
	Going out with family and friends/Social anxiety	20	15.3%
	Low self-confidence/self-esteem	9	6.9%
	Feeling exhausted easily	5	3.8%
	Nervous/anxiety/feeling insecure	16	12.2%
	Depression	7	5.3%
	Studying	1	0.8%
	Prefer not to mention	54	41.2%
d. Are there things you avoid because of how you look?	Yes	311	27.6%
	No	815	72.4%
If yes, what are they?* (N=311)	Clothes	86	27.7%
	Eating	11	3.5%
	Taking and publishing photos	30	9.6%
	Socializing/dating/going out with family/friends	65	20.9%
	Swimming/hobbies	11	3.5%
	Cosmetics/hairstyles/showing body	19	6.1%
	Prefer not to mention	122	39.2%
4. On an average day, how much time do you usually spend thinking about how you look?	>= 1 h	954	84.7%
	< 1 h	172	15.3%
5. Is your main concern with how you look that you aren't thin enough or that you might get too fat?	Yes	506	44.9%
	No	620	55.1%

Table 3. Summary of body dysmorphic disorder questionnaire (BDDQ). *Multiple response analysis.

	BDD (N=71)				Non-BDD (N=1055)				
	Mean	SD	N	%	Mean	SD	N	%	p-value
Age	20.8	1.7			20.4	1.3			**<0.001***
Gender									0.93
Male			26	36.6%			381	36.1%	
Female			45	63.4%			674	63.9%	
Governorate									**0.03***
Dakahlia			9	12.7%			318	30.1%	**0.002***
Cairo			24	33.8%			258	24.5%	0.08
Qena			20	28.2%			140	13.3%	**<0.001***
Damietta			4	5.6%			78	7.4%	0.58
Qalyubia			2	2.8%			36	3.4%	0.79
Giza			1	1.4%			44	4.2%	0.25
Sharqia			3	4.2%			26	2.5%	0.37
Kafr El-Sheikh			0	0.0%			26	2.5%	0.18
Gharbia			1	1.4%			20	1.9%	0.77
Port Said			2	2.8%			17	1.6%	0.45
Isamailia			0	0.0%			21	2.0%	0.23
Assuit			2	2.8%			19	1.8%	0.54
Beni Sweif			1	1.4%			14	1.3%	0.96
Alexandria			0	0.0%			8	0.8%	0.46
Suez			1	1.4%			7	0.7%	0.47
Sinai			0	0.0%			7	0.7%	0.49
Others			1	1.4%			16	1.5%	0.94
Economic status									0.06
High			9	12.7%			63	6.0%	**0.03***
Middle			62	87.3%			982	93.1%	0.07
Low			0	0.0%			10	0.9%	0.41
Marital status									0.25
Single			69	97.2%			1045	99.1%	0.14
Married			2	2.8%			7	0.7%	**0.05***
Divorced			0	0.0%			1	0.1%	0.8
Widowed			0	0.0%			2	0.2%	0.71
Residence									**0.03***
Urban			42	59.2%			751	71.2%	
Rural			29	40.8%			304	28.8%	
Which social media platform do you use the most?									
Facebook			46	64.8%			580	55.0%	0.11
WhatsApp			46	64.8%			683	64.7%	0.99
Instagram			37	52.1%			564	53.5%	0.83
Twitter			11	15.5%			192	18.2%	0.57
Snapchat			12	16.9%			178	16.9%	1.00
TikTok			21	29.6%			311	29.5%	0.99
YouTube			26	36.6%			459	43.5%	0.26
Linked in			2	2.8%			33	3.1%	0.88
Telegram			3	4.2%			36	3.4%	0.72
Other platforms			2	2.8%			16	1.5%	0.40
Average time spent on social media per day									0.67
>7 h			33	46.5%			530	50.2%	0.54
4–7 h			23	32.4%			351	33.3%	0.88
1–3 h			14	19.7%			153	14.5%	0.23
<1 h			1	1.4%			21	2.0%	0.73
To what extent do you take selfies?									1.00
Always			30	42.3%			454	43.0%	0.9
Sometimes			29	40.8%			425	40.3%	0.93
Rarely			6	8.5%			86	8.2%	0.93
Continued									

	BDD (N=71)				Non-BDD (N=1055)				
	Mean	SD	N	%	Mean	SD	N	%	p-value
Never			6	8.5%			90	8.5%	0.98
To what extent do you use filters to edit selfies?									0.47
Always			23	32.4%			325	30.8%	0.78
Sometimes			20	28.2%			301	28.5%	0.95
Rarely			17	23.9%			319	30.2%	0.26
Never			11	15.5%			110	10.4%	0.18
To what extent do you share selfies with others?									0.64
Always			31	43.7%			415	39.3%	0.47
Sometimes			23	32.4%			340	32.2%	0.98
Rarely			15	21.1%			233	22.1%	0.85
Never			2	2.8%			67	6.4%	0.23

Table 4. Associations between sociodemographics and social media practices and BDD. Categorical data are described by number and % calculated by column. *Significant.

	OR	P-value.	95% CI
Age group			
<=21	2.56	0.004*	1.36–4.82
>21	R	R	R
Governorate			
Dakahlia	0.34	0.003*	0.17–0.69
Other Governorates	R	R	R
Qena	2.56	0.001*	1.48–4.43
Other Governorates	R	R	R
Economic status			
High	2.29	0.03*	1.09–4.81
Middle/low	R	R	R
Residence			
Rural	1.71	0.03*	1.04–2.79
Urban	R	R	R

Table 5. Significant predictors of BDD. *Significant. *OR* Odds Ratio, *CI* Confidence Interval, *R* Reference.

but growing body of research on the association between social media use and body dysmorphic symptoms. To the best of our knowledge, this is the first study to look at the link between social media use and BDD among Egyptian medical students. Our sample of 1126 undergraduate medical students had an average age of 20.8 years. The study revealed that 6.3% of individuals had BDD, significantly higher than the global norm of 2.2% in adolescents, 1.9% in adults, and 3.3% in students[10]. However, this finding aligns more closely with findings from non-Western regions, such as Saudi Arabia (8.8% in Jeddah) and Benin (10.31% at the University of Parakou)[11,12], it contrasts with lower rates reported in Asian contexts. For example, a study of Chinese medical students found a BDD prevalence of 1.3%[13], while Western epidemiologic data suggest general population rates of 1.7–2.9%[12,14].

This disparity may reflect methodological differences (e.g., diagnostic tools, sampling strategies) or sociocultural factors. In Asian medical schools, academic pressures are intense, yet BDD rates remain relatively low compared to Egypt and Africa. This could stem from cultural variations in beauty standards—for instance, East Asian cultures often emphasize facial features or skin tone[13], while Middle Eastern and African contexts may prioritize body shape or hair[11,12]. Additionally, social media's role in amplifying appearance ideals appears more pronounced in regions with rapidly digitizing populations, such as Egypt and Saudi Arabia, where platforms like Instagram and Snapchat are widely used for image-centric interactions. Western studies of medical students are limited, but general population data suggest BDD prevalence is lower than in our sample. However, Western medical students face comparable academic stressors, which are known to exacerbate body image concerns[13]. The higher prevalence in our study and similar non-Western settings may also reflect underdiagnoses in Western contexts due to greater mental health literacy or differences in help-seeking behavior[12,14].

For instance, the complex interactions of cultural, social, and psychological factors unique to the Egyptian context can explain this high percentage. Physical appearance is greatly prized in Egyptian society, particularly in terms of marriageability and social status. The 2023 Alexandria University study confirmed that 36.6% of students fixated on skin imperfections and 36.2% on belly size—traits subject to extreme scrutiny within Egyptian

		N	%
What strategies do you use to cope with negative feelings about your body image due to social media?*	Limiting social media usage	331	29.4%
	Unfollowing accounts that promote unrealistic body standards	343	30.5%
	Seeking support from friends/family	269	23.9%
	Consulting a mental health professional	97	8.6%
	Engaging in positive self-talk	445	39.5%
	Participating in offline activities/hobbies	353	31.3%
	Watching shows/podcasts	4	0.4%
	Prayer/Quran/Meditate/self-embracing	57	5.1%
	Health care/improvement	40	3.6%
	Nothing	72	6.4%
What measures do you think social media platforms should take to address body dysmorphia?*	Promoting body positivity	536	47.6%
	Banning photo editing apps	282	25.0%
	Implementing mental health support features	446	39.6%
	Educating users about the risks of body dysmorphia	616	54.7%
	Restricting content that promotes unrealistic body standards	510	45.3%
	Providing resources and support for those affected	484	43.0%
	Prevent bullying/body shaming	2	0.2%
	Religious teaching/self-embracing	12	1.1%
	Nothing	30	2.7%
Would you support initiatives aimed at raising awareness about social media-related body dysmorphia?	Strongly support	550	48.8%
	Support	385	34.2%
	Neutral	161	14.3%
	Oppose	17	1.5%
	Strongly oppose	13	1.2%

Table 6. Adaptive mechanisms and their attitudes. *Multiple response analysis.

cultural standards[15]. This anxiety is fueled by traditional beauty standards that identify physical beauty and moral virtue, a subject examined in a 2022 study of Egyptian Muslim women[16]. Participants reported intense pressure to conform to limiting beauty standards, as deviation risks social exclusion or reduced marriage prospects[16]. In addition, the prevalence of image-sharing platforms like Instagram and TikTok has only served to exacerbate Egypt's BDD symptoms. Researchers at Alexandria University confirmed a dose-response relationship: every additional hour per day spent on social media tripled the risk of BDD symptoms (OR = 2.926)[15]. Egyptian women are faced with conflicting pressures: with traditional modesty standards pitted against modern beauty standards as shown in media. The 2022 survey of plastic surgery discovered that 41% of Egyptian women presenting for cosmetic surgery cited "marriage market competitiveness" as a primary reason, many concomitant with female gender role stress (FGRS)[16]. Egypt's BDD prevalence may be an artifact of underdiagnoses, not differences in actual incidence. This treatment avoidance persists: the 2023 Alexandria cohort illustrated that help-resistance tripled BDD risk (OR = 3.327)[16].

In line with previous reports[10], 63.4% of persons with BDD were female. Most medical students with BDD were single urban residents from Cairo, Qena, and Dakahlia governorates with a middle-level economic situation. Notably, social media platforms that rely mostly on text (like Facebook and WhatsApp) rather than images (like Instagram and YouTube) were highly linked to BDD. This result contradicts previous research[17–19]. This is because, in Egypt, text-based sites like WhatsApp are focal points of daily communication and social interaction. These sites provide opportunities for incessant appearance-related conversation—e.g., dieting, exercise, or appearance criticism—thus potentially increasing body dissatisfaction even without visual exposure. This is supported by[20], which posits that the use of social media can impact mental health in different ways. Compared to the relatively passive social comparison which is typical of image-based websites, the explicit, personalized censure which is common in text-based communication could be more emotionally charged and trigger BDD-related issues[20]. Moreover, the academic pressure of medical students could uniquely combine with their utilization of social media. Given the intensity of their curriculum, medical students may have to rely heavily on text-based platforms like WhatsApp for organization and support in studying, thus possibly indirectly exacerbating stress and consequently BDD symptoms. Finally, our study involved platform frequencies of use, not types of content consumed. Our participants might have used image-based sites in more passive ways (e.g., watching educational videos on YouTube), and engaged actively in appearance discourses on text-based sites. People with BDD used social media on average for a lot longer than people without the disorder. Consistent with Alsaidan et al.[18], the majority used social media platforms for more than 4 h each day. At the same time, Ateq et al.[8] reported that the majority of participants spent < 4 h per day. Of the participants, 55.9% were incredibly concerned about their appearance. In the current study, the most worrisome body regions were the face (16.7%), belly (9.7%), and nose (7.9%). Concerns about abdominal appearance can be explained by the high prevalence of abdominal obesity and metabolic syndrome due to the socioeconomic, lifestyle, and nutritional changes that have

been taking place in the Egyptian community and some other Arab countries toward the unhealthy pattern[21]. Cultural and social pressures can exacerbate facial concerns, especially in females, increasing the likelihood of developing BDD. Contrary to our study, these studies[18,22–24] reported that skin and hair were the areas of highest concern. Only 11.6% of individuals claimed that their looks had caused problems in their community. In line with this Saudi study[18], bullying and social anxiety were the most common issues at school or work, accounting for 2.4% and 1.8%, respectively.

Certain clothes, taking and publishing images, and socializing were the key acts avoided due to their appearance, resulting in various negative consequences: (1) Increased social withdrawal, (2) Reinforced negative self-image, (3) Obsessive checking and validation seeking, (4) Negative impact on academic performance, (5) Low self-esteem and professional confidence, (6) Increased risk of depression and anxiety. Social media can have varying effects on body image. Selfies, or frontal photos of oneself, can be taken with apps like Instagram and Snapchat and edited with a range of striking filters. To enhance one's appearance, most filters alter facial features, usually in an exaggerated manner. People who have these traits may experience ongoing body dissatisfaction. Social media exposure to beauty standards exacerbates body image problems, per a recent comprehensive assessment of experimental investigations[25]. Additionally, a study[26] carried out in psychiatric settings found that frequent selfie use has been connected to appearance concerns. Concerns about physical appearance increased as a result of redefining selfies, per another systematic review[27]. Another comprehensive analysis found that reframing selfies increased concerns about physical appearance[27]. The majority of respondents cited positive self-talk, offline hobbies and activities, unfollowing accounts that promote unrealistic body ideals, and restricting social media use as coping techniques for negative body image. When using photo editing apps, social media users pay greater attention to how they look, which promotes acceptance of fake beauty[28]. Frequent usage of filters and selfies can lead to an obsession with unrealistic beauty standards and a desire to alter one's appearance.

Limitations and recommendations

Limitations should be applied while evaluating the findings of this study. The study's cross-sectional design precludes drawing any conclusions regarding the causal relationship between its variables. Nonetheless, experimental research has demonstrated a causal relationship between BDD and social media[29]. Our study's second weakness is the convenience sampling strategy. The use of convenience sampling limits the generalizability of our findings, as certain governorates or groups may have been over- or under-represented. Thus, we recommend future studies employ probability-based sampling methods, such as stratified or random sampling, to ensure more balanced and representative samples. Since Facebook is the main communication tool utilized by the vast majority of men, women, and both younger and older populations in Egypt, we specifically employed it to reach all demographic groups. Furthermore, a far larger sample size than the suggested predicted power was used for the survey. It may be the goal of future research to include more guys in their sampling. Cross-sectional studies that use self-reported responses have an additional inherent constraint that could compromise response accuracy. Regarding the exclusion of non-social media users and the potential introduction of selection bias, this exclusion limits the generalizability of our findings to the broader population. We further suggest that future research explore BDD prevalence in both social media users and non-users to provide a more comprehensive understanding. This can be explained by the fact that our study specifically aims to assess the correlation between exposure to idealized beauty standards shaped by social media and body dysmorphic disorder (BDD) symptoms. Since social media is the primary source of the beauty standards under investigation, non-users would not have the same level of exposure. Thus, our findings are specific to social media users and may not be generalizable to the entire population. We excluded participants who self-reported having a mental health disorder because the study aimed to isolate the impact of social media on BDD in individuals without pre-existing mental health conditions that could significantly influence body image. We acknowledge that this exclusion significantly limits the generalizability of our findings and that our results only apply to individuals without self-reported mental health disorders. Thus, future research to investigate the relationship between social media, BDD, and mental health in a broader population is recommended. According to the limitations of our study population, our study was conducted among Egyptian medical students, a specialized group that may not be representative of the general population. The demanding academic environment could limit their social media use compared to other groups, potentially underestimating the impact of social media on body image and body dysmorphic disorder (BDD). Additionally, the influence of socioeconomic factors, age range, and cultural context on perceptions of beauty standards emphasizes that our findings may not be directly transferable to other populations. Despite these limitations, we suggest that the underlying relationships observed may still be analytically generalized to other groups facing similar pressures and call for future research to explore these dynamics in more diverse populations, including those with mental health disorders, to enhance our understanding of the complex interplay between social media, body image, and BDD.

Regarding the strength of the study, focusing on medical students allows for a specific demographic that is likely to be aware of mental health issues, potentially leading to more insightful responses. We make sure to avoid suggestive language and any leading questions. In addition, we have delivered the survey anonymously through the web to avoid observers' bias and to increase confidentiality and privacy. We also ensured that the survey was short to avoid responder bias due to fatigue. Examining BDD concerning social media use is particularly relevant in today's digital age, where social media can significantly impact self-image and mental health. Furthermore, the questionnaire can yield quantifiable data that can be statistically analyzed, allowing for clear associations and trends to be identified. Respondents may feel more comfortable providing honest answers about sensitive topics like body image and mental health in an anonymous survey than in a face-to-face interview. We recommend a future study that compares between body concern questionnaire (BCQ) and BDDQ in terms of sensitivity and specificity.

Conclusion

Our study found that BDD is highly prevalent among social media users, especially text-based platforms. The prevalence of BDD among Egyptian medical students is 6.7%, which is higher than worldwide. Interestingly, Egyptian medical students enrolled in our study believe that promoting body positivity, educating users about the risks of body dysmorphia, restricting content that promotes unrealistic body standards, and providing resources and support for those affected, respectively, are the critical measures that social media platforms should take to address body dysmorphia. Furthermore, they strongly agree with initiatives aimed at raising awareness about social media-related body dysmorphia. Most participants with issues with their appearance do not like their faces, their abdomen, and noses. Among those who suffered in school or work, the majority reported bullying and social anxiety. This research is significant in its offering of insight into the traits and social media behaviors of Egyptian medical students, and their possible link to Body Dysmorphic Disorder (BDD). Our results indicate statistically significant differences between the BDD and non-BDD groups about age and governorate, with the BDD group being slightly older overall and having clear-cut distributions by different governorates. In addition, a strong association was found between BDD and economic status and place of residence. While social media usage patterns, including platform usage, time, selfie behavior, filter use, and posting frequency, did not show statistically significant differences between the two groups, the trends observed are worthy of further investigation. The high prevalence of social media usage and selfie retouching among medical students highlights the potential effect of digitally altered images on body image perception. More comprehensive research involving larger samples and more subtle assessments of social media use is needed to further clarify the dynamic interplay among social media, sociocultural factors, and the risk of BDD in this population. Last but not least, the findings of these studies underscore the importance of raising awareness regarding body image issues and enhancing media literacy among Egyptian youth.

Data availability

The datasets used and/or analysed during the current study available from the corresponding author on reasonable request.

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Author contributions
All authors reviewed the literature. Ahmed. R. A. Moustafa, Anwar M. Bshar and Mohammed N. Abdelaziz have investigated the research and performed data collection. Hajer Azzam and Mohammed N. Abdelaziz performed the data analysis. Ismail. S. Ismail, Mohammed. N. Abdelaziz, Hajer Azzam, Ahmed R. A. Moustafa, and Anwar. M. Bshar have written the first versions. Ismail. S. Ismail, Mohammed N. Abdelaziz, Hajer Azzam, Ahmed R. A. Moustafa, Anwar. M. Bshar and Omnia Yousry Elhadidy reviewed and edited the writing. Mohammed. N. Abdelaziz is the corresponding author. Supervised by Omnia Yousry Elhadidy.

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Declarations

Competing interests
The authors declare no competing interests.

Ethical approval
The Institutional Review Board of Medical Research Ethics at Mansoura University's Faculty of Medicine approved the study protocol (IRB code: R.24.05.2641.R2). All participants filled out informed consent forms and were assured of the confidentiality of the study, together with the right to withdraw or refuse to answer the questionnaire before the study started. All study procedures were performed by the Declaration of Helsinki.

Additional information
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Risk Factors That Predict Future Onset of Anorexia Nervosa, Bulimia Nervosa, Binge Eating Disorder and Purging Disorder in

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Because very few prospective studies have factors that predicted future onset of thresh old anorexia nervosa (AN), bulimia nervosa eating disorder (BED), and purging disorder lyzed prospective data collected from a large c lescent girls followed over an 8-year period to advance knowledge about risk factor specificity. Adolescent girls recruited from middle schools in Texas ($N = 492$; M age = 13.02 [$SD = 0.73$], age range = 11–15) completed questionnaires assessing risk factors at baseline and diagnostic interviews assessing eating disorders annually over 8 years. Only low BMI predicted future AN onset. Pressure to be thin, thin-ideal internalization, body dissatisfaction, negative emotionality, low parent support, and modeling of eating pathology predicted future BN onset. Pressure to be thin, thin-ideal internalization, negative emotionality, low parent support, and modeling of eating pathology predicted future BED onset. Pressure to be thin, body dissatisfaction, dietary restraint, low parent support, modeling of eating pathology, and high BMI predicted future PD onset. Predictive effects were medium-to-large. Results support etiological theories of eating disorders that postulate the pursuit of the thin ideal, body dissatisfaction, negative affect, dietary restraint, and interpersonal issues increase evidence that girls with whereas girls with high novel. Although several of BN, BED, and PD, N are qualitatively dis- ther.

Keywords: risk factors; anorexia nervosa; bulimia nervosa; binge eating disorder; purging disorder

This research was supported by NIH grants MH01708 and MH64560.
The authors declare no conflicts of interest.
The datasets analyzed in the current study are available from the corresponding author on reasonable request.

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PROSPECTIVE STUDIES examining anorexia nervosa (AN), bulimia nervosa (BN), binge eating disorder (BED), as well as subthreshold cases of these eating disorders and purging disorder (PD), which are classified as Other Specified Feeding and Eating Disorders (OSFED) per DSM-5 (American Psychiatric Association, 2013), in representative samples indicate that adolescent girls with threshold and subthreshold eating disorders experience functional impairment, distress, suicidality, unhealthy body weights, and mental health services utilization (Allen et al., 2013; Smink et al., 2012; Stice et al., 2013). Moreover, approximately 30% of those with subthreshold eating disorders later develop threshold eating disorders (Glazer et al., 2019) and one-third of those seeking eating disorder treatment have an OSFED (Mancuso et al., 2015; Thomas et al., 2015), further underscoring the importance of including OSFED in studies of eating disorders.

Unfortunately, even the most effective eating disorder prevention program has only prevented 62% of cases that emerged in control conditions on average (Stice et al., 2021a). One possible reason for the

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Risk Factors That Predict Future Onset of Anorexia Nervosa, Bulimia Nervosa, Binge Eating Disorder, and Purging Disorder in Adolescent Girls

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Because very few prospective studies have identified risk factors that predicted future onset of threshold/subthreshold anorexia nervosa (AN), bulimia nervosa (BN), binge eating disorder (BED), and purging disorder (PD), we analyzed prospective data collected from a large cohort of adolescent girls followed over an 8-year period to advance knowledge about risk factor specificity. Adolescent girls recruited from middle schools in Texas ($N = 492$; M age = 13.02 [$SD = 0.73$], age range = 11–15) completed questionnaires assessing risk factors at baseline and diagnostic interviews assessing eating disorders annually over 8 years. Only low BMI predicted future AN onset. Pressure to be thin, thin-ideal internalization, body dissatisfaction, negative emotionality, low parent support, and modeling of eating pathology predicted future BN onset. Pressure to be thin, thin-ideal internalization, negative emotionality, low parent support, and modeling of eating pathology predicted future BED onset. Pressure to be thin, body dissatisfaction, dietary restraint, low parent support, modeling of eating pathology, and high BMI predicted future PD onset. Predictive effects were medium-to-large. Results support etiological theories of eating disorders that postulate the pursuit of the thin ideal, body dissatisfaction, negative affect, dietary restraint, and interpersonal issues increase risk for most eating disorders. The evidence that girls with low body weight are at risk for AN, whereas girls with high body weight are at risk for PD are novel. Although several risk factors predicted future onset of BN, BED, and PD, results suggest that risk factors for AN are qualitatively distinct and should be investigated further.

Keywords: risk factors; anorexia nervosa; bulimia nervosa; binge eating disorder; purging disorder

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The authors declare no conflicts of interest.
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Prospective studies examining anorexia nervosa (AN), bulimia nervosa (BN), binge eating disorder (BED), as well as subthreshold cases of these eating disorders and purging disorder (PD), which are classified as Other Specified Feeding and Eating Disorders (OSFED) per DSM-5 (American Psychiatric Association, 2013), in representative samples indicate that adolescent girls with threshold and subthreshold eating disorders experience functional impairment, distress, suicidality, unhealthy body weights, and mental health services utilization (Allen et al., 2013; Smink et al., 2012; Stice et al., 2013). Moreover, approximately 30% of those with subthreshold eating disorders later develop threshold eating disorders (Glazer et al., 2019) and one-third of those seeking eating disorder treatment have an OSFED (Mancuso et al., 2015; Thomas et al., 2015), further underscoring the importance of including OSFED in studies of eating disorders.

Unfortunately, even the most effective eating disorder prevention program has only prevented 62% of cases that emerged in control conditions on average (Stice et al., 2021a). One possible reason for the

scarcity of effective prevention programs is that only a few prospective studies have identified baseline risk factors that predict future onset of eating disorders among individuals who do not have eating disorders at baseline. Methodologists argue that the term "risk factor" should be reserved for variables shown to predict future onset of a disorder among individuals without the disorder when the putative risk factors were assessed because this procedure provides the strongest evidence that elevations in the risk factors temporally precede disorder onset (Kraemer et al., 1997). A few studies have found that pressure for thinness, pursuit of the thin ideal, body dissatisfaction, parental overweight, dieting, negative affect, and female sex predict future onset of any eating disorder (Allen et al., 2014; Dakanalis et al., 2017; Jacobi et al., 2011; Rohde et al., 2015). Even fewer studies have identified risk factors that predict future onset of specific eating disorders, which limits knowledge of risk factor specificity. Low body mass index (BMI), weight suppression, weight/shape overvaluation, fear of weight gain, negative affect, and psychosocial impairment have predicted onset of AN in a high-risk sample (Stice et al., 2017, 2020, 2021b). Pressure for thinness, pursuit of the thin ideal, weight/shape overvaluation, fear of weight gain, body dissatisfaction, feeling fat, overeating, binge eating, dieting, weight suppression, compensatory weight-control behaviors, negative affect, and psychosocial impairment have predicted onset of BN in representative and high-risk samples (Killen et al., 1996; Patton et al., 1999; Stice et al., 2017, 2020, 2021b). Pursuit of the thin ideal, weight/shape overvaluation, fear of weight gain, body dissatisfaction, feeling fat, dieting, binge eating, negative affect, and psychosocial impairment have predicted onset of BED in a high-risk sample (Stice et al., 2017, 2021b). Last, pursuit of the thin ideal, body dissatisfaction, dieting, negative affect, binge eating, compensatory weight-control behaviors, weight/shape overvaluation, fear of weight gain, feeling fat, and psychosocial impairment have predicted future onset of PD in a high-risk sample (Stice et al., 2017, 2020, 2021b).

Hence, studies have advanced knowledge regarding risk factors for eating disorders, but they mostly examined at-risk and/or older samples or did not separately examine risk factors for each disorder type. Moreover, only one high-risk data set was powered to detect risk factors predicting future onset of each type of eating disorder (Stice et al., 2017, 2020, 2021b), but it did not follow participants throughout adolescence, which is the peak period for eating disorder onset (Stice et al., 2013). Accordingly, our primary aim was to identify risk factors that predict future onset of threshold or subthreshold AN, BN, BED, or PD that included both standard eating disorders and OSFED, using data from a large community sample of adolescent girls without eating disorders at baseline who were followed over an 8-year period. It seemed to be best to examine whether the baseline risk factors predicted the future onset of each eating disorder over the full follow-up period because this approach maximized the number of onset cases in the models, thereby optimizing power. This decision was primarily driven by the argument from methodologists that analyses testing whether a baseline risk factor predicts the future onset of new psychiatric disorders in a sample free of the disorders at baseline provide the most compelling evidence of temporal precedence (Kraemer et al., 2001). Furthermore, we were concerned that lagged-predictor models would be less stable due to the small number of cases showing the onset of each eating disorder each year during the 7-year follow-up.

We examined which of the following risk factors would have the strongest univariate predictive effects for each disorder type—pressure to be thin, thin-ideal internalization, body dissatisfaction, dietary restraint, negative emotionality, parent social support, peer social support, modeling of pathological eating (of family and peers), and BMI. They were selectively examined because of the prior findings as well as theoretical models to explain developmental mechanism of eating disorders. In particular, the dual pathway model (Stice & van Ryzin, 2019) postulates that pursuit of the thin beauty ideal leads to body dissatisfaction, which increases risk for dietary restraint and negative affect, which predict onset of bulimic-spectrum eating disorders. In addition, research has reported that individuals with AN are prone to negative emotionality and utilize maladaptive strategies, such as dietary restriction, to regulate their negative emotions (Haynos & Fruzzetti, 2011). Treasure et al. (2020) have also proposed that interpersonal difficulties act as both risk factors and secondary consequences of AN. Moreover, the emotional dysregulation model of BN (Lavender et al., 2016) postulates that females may engage in binge eating and/or weight-control compensatory behaviors in response to negative emotions. Last, the interpersonal difficulty model of eating disorders (Arcelus et al., 2013) states that psychosocial impairment in interpersonal functioning predicts eating disorders characterized by binge eating and/or purging behavior as they may serve as an emotional catharsis for interpersonal problems.

We hypothesized that pressure to be thin, thin-ideal internalization, body dissatisfaction, dietary restraint, and increased BMI would predict eating disorders, especially AN and BN, whose prodromal symptoms include the perceived importance of body weight/shape (Yamamiya et al., 2022). We also hypothesized that negative emotionality, low parent social support, low peer social support, and modeling of pathological eating (of family and peers) would predict eating disorders, especially BN, BED, and PD, because binge eating and purging behaviors were performed to cope with negative emotions and interpersonal problems. Our secondary aim was to examine unique predictive effects of risk factors to predict each eating disorder when multiple risk factors simultaneously predicted an eating disorder.

Method

PARTICIPANTS AND PROCEDURES

We collected data from 492 adolescent girls. Participants were recruited from four public and four private middle schools in Texas. An informed consent letter and self-addressed return envelope were sent to parents of girls who went to the schools. The purpose of the study was described as an investigation of physical and mental health of adolescent girls. The return rate was 56%, which was similar to the rates reported in other longitudinal studies (e.g., Striegel-Moore et al., 2003). The average age of the participants was 13.02 years ($SD = .73$; range = 11–15) at baseline, and 67.7% of the participants self-identified as White, 18.1% Hispanic, 7.3% Black, 1.6%, Asian, 0.8% Native American, and 3.8% other. Among those who reported parental education, 35% of parents were college graduates and 15% of parents had an advanced degree. Prior analyses confirmed that this sample was representative in terms of race/ethnicity and socioeconomic status to the sampling frame from which participants were recruited (Stice et al., 2009).

Participants completed a series of questionnaires and a diagnostic interview, then had their weight and height measured by female assessors in a lab. The baseline assessment took place in 1999 and 2000, and the assessment procedure was repeated for the following 7 years. Participants were offered a $15 gift certificate to a book and music store as compensation for completing each assessment. Moreover, we collected contact information for three people who would always know how to reach the participant, which has helped us minimize attrition.

MEASURES

Eating Pathology

The semistructured Eating Disorder Diagnostic Interview (EDDI; Stice et al., 2017) assessed eating-disorder symptoms over the past 3 months at baseline (Wave 1) and since the last interview at each annual follow-up on a month-by-month basis using time-line follow-back over the next 7 years (Waves 2–8). We used DSM-5 criteria for threshold/subthreshold eating disorders (see Table 1 for diagnostic criteria). The EDDI showed high test-retest reliability ($k = .96$) and inter-rater reliability ($k = .86$) in this sample. Further, participants with threshold/subthreshold DSM-5 EDDI-diagnosed eating disorders showed greater functional impairment, distress, and mental health treatment than those without (Stice et al., 2013). For the present study, female assessors with a B.A./B.S., M.A., or Ph.D. in psychology were required to receive instruction in structured interview skills, learn diagnostic criteria for eating disorders, observe simulated interviews, and role-play interviews in a 24-hour training session. They were also required to demonstrate an inter-rater agreement ($k > .80$) with supervisors on 12 tape-recorded interviews prior to collecting data as well as complete annual refresher training to further establish the reliability and validity of the assessment across 7 years.

Pressure to Be Thin

The 10-item Perceived Sociocultural Pressure Scale (Stice & Bearman, 2001) assessed to what extent a participant perceived pressure to be thin from family, peers, and the media (e.g., "I've felt pressure from my friends to lose weight"). This scale has shown internal consistency ($\alpha = .88$), 2-week test-retest reliability ($r = .93$), and predictive validity of the future occurrence of bulimic symptoms (Stice et al., 2002). Cronbach's $\alpha = .83$ at baseline.

Thin-Ideal Internalization

The 6-item Ideal-Body Stereotype Scale–Revised (Stice et al., 2017) assessed pursuit of the thin ideal (e.g., "Slender women are more attractive"). It has shown internal consistency ($\alpha = .91$), 2-week test–retest reliability ($r = .80$), and predictive validity for future BN, BED, and PD onset (Stice et al., 2017). Cronbach's $\alpha = .81$ at baseline.

Body Dissatisfaction

The 9-item Body Dissatisfaction Scale (Berscheid et al., 1973) assessed dissatisfaction with various body parts (e.g., "How satisfied are you with your: [Weight]"). It has shown internal consistency ($\alpha = .94$), 3-week test–retest reliability ($r = .90$), and predictive validity for future BN, BED, and

Table 1
Classification Criteria of Threshold and Subthreshold Eating Disorders

Eating disorders	Threshold criteria	Subthreshold criteria
AN	Body mass index (BMI) less than 85% of the median expected for age and sex	BMI between 90% and 85% of that expected for age and sex
	Definite fear of weight gain more than 75% of the days for at least 3 months	Definite fear of weight gain more than 25% of the days for at least 3 months
	Weight and shape being one of the main aspects of self-evaluation	Weight and shape being one of the main aspects of self-evaluation
BN	At least 4 uncontrollable binge-eating episodes per month for at least 3 months	At least 2 uncontrollable binge-eating episodes per month for at least 3 months or at least 6 episodes over a shorter period
	At least 4 compensatory behavior episodes per month for at least 3 months	At least 2 compensatory behavior episodes (i.e., self-induced vomiting, laxatives or diuretic use, fasting, and excessive exercise to compensate for overeating) per month for at least 3 months or at least 6 episodes over a shorter period
	Weight and shape being definitely one of the main aspects of self-evaluation	Weight and shape being definitely one of the main aspects of self-evaluation
BED	At least 4 uncontrollable binge-eating episodes/days per month for at least 3 months	At least 2 uncontrollable binge-eating episodes/days per month for at least 3 months or at least 6 episodes over a shorter period
	Fewer than 1 compensatory behavior on average per month during this period	Fewer than 1 compensatory behavior on average per month during this period
	Marked distress about binge eating	Marked distress about binge eating
	Binge eating characterized by 3 or more of the following: rapid eating; eating until uncomfortably full; eating large amounts when not physically hungry; eating alone because of embarrassment; feeling disgusted, depressed, or guilty after overeating	Binge eating characterized by 3 or more of the following: rapid eating; eating until uncomfortably full; eating large amounts when not physically hungry; eating alone because of embarrassment; feeling disgusted, depressed, or guilty after overeating
PD	At least 4 episodes of self-induced vomiting or diuretic/laxative use for weight control purposes per month for at least 3 months	At least 2 episodes of self-induced vomiting or diuretic/laxative use for weight control purposes per month for at least 3 months or at least 6 episodes over a shorter period
	Fewer than 1 uncontrollable binge-eating episode on average per month during this period	Fewer than 1 uncontrollable binge-eating episode on average per month during this period
	Weight and shape being one of the main aspects of self-evaluation	Weight and shape being one of the main aspects of self-evaluation

Note. AN = anorexia nervosa; BN = bulimia nervosa; BED = binge eating disorder; PD = purging disorder.

PD onset, (Stice et al., 2017). Cronbach's $\alpha = .94$ at baseline.

Dietary Restraint
The 9-item Dutch Restrained Eating Scale (van Strien et al., 1986) assessed the frequency of a participant's dieting behaviors (e.g., "I would be happy if I were thin"). It has shown internal consistency ($\alpha = .95$), 2-week test–retest reliability ($r = .82$), and predictive validity for future BN, BED, and PD onset (Stice et al., 2017; van Strien et al., 1986). Cronbach's $\alpha = .91$ at baseline.

Negative Emotionality
The 12-item Buss and Plomin's Emotionality Scale (1984) assessed to what extent a participant was prone to experience various negative emotions (e.g., "I frequently get upset"). This scale has shown predictive validity for the future increases in bulimic symptoms (Stice, 2001) and convergent

validity with other measures of negative emotionality (Patrick et al., 2002). Cronbach's $\alpha = .80$ at baseline.

Perceived Parent Support and Peer Support
Perceived social support from parent(s) and peers was assessed by 12 items from the Network of Relationships Inventory (Furman & Buhrmester, 1985). The items assessed to what extent a respondent perceived companionship, guidance, closeness, affection, admiration, and dependable alliance from parent(s) and peers (e.g., "I could count on my parent(s) to be there when I needed them"). The original scale has shown internal consistency ($\alpha = .80$), 1-year test-retest reliability ($r = .66$–$.75$), and convergent and criterion validities (Furman, 1996; Furman & Buhrmester, 1985). Cronbach's $\alpha = .87$ for parent support and .86 for peer support at baseline.

Modeling of Eating Pathology
Perceived family and peer modeling of pathological eating was assessed with the Eating Pathology Modeling scale (Stice, 1998). A sample item is: "One or more of my family members [or my friends] has fasted, exercised excessively, vomited, or used laxatives or diuretics to lose weight." The scale showed a 2-week test-retest reliability ($rs = .82$ for family modeling and .77 for peers modeling) and convergent validity (Stice, 1998). Cronbach's $\alpha = .77$ at baseline.

Standardized Body Mass Index (zBMI)
First, BMI (kg/m^2; Pietrobelli et al., 1998) was calculated to reflect height-adjusted weight. Height was measured to the nearest millimeter by using portable stadiometers and weight was measured to the nearest 0.1 kg by using digital scales while participants wore light indoor clothing without shoes or coats. Height and weight were repeated twice and averaged. BMI has shown convergent validity ($r = .80$–$.90$) with direct measures of body fat (Pietrobelli et al., 1998) and predictive validity for future onset of AN (Stice et al., 2017). Then, given the known limitations of BMI within participants who were still developing physically, we converted BMI to zBMI and analyzed the predictive effects of zBMI values instead of raw BMI values.

Statistical Methods

RELATION OF RISK FACTORS TO FUTURE ONSET OF EATING DISORDERS

We examined if risk factors assessed at baseline univariately predicted the later onset of threshold/-subthreshold AN, BN, BED, or PD using the Cox proportional hazard modeling analyses. All predictor variables were treated as continuous variables and standardized. When HR is below 1.0, it indicates a negative relationship, and when it is above 1.0, it indicates a positive relationship. According to Azuero (2016), small, medium, and large HRs are 1.3, 1.9, and 2.8, respectively. However, this pertains to situations when the effects of a dichotomous independent variable are examined, whereas our predictor variables were continuous. Therefore, it might be best to refer to *ds* as effect sizes. According to Cohen's criteria (Cohen, 1992), *ds* of 0.1, 0.3, and 0.5 represented small, medium, and large effects, respectively (Azuero, 2016). When multiple risk factors simultaneously predicted an eating disorder, we explored unique predictive effects of risk factors on each eating disorder by using multivariate backward stepwise logistic regressions. All analyses were tested with SPSS ver. 26 and R (R Core Team, 2020).

MISSINGNESS AND ATTRITION

Missing data occurred at the baseline assessment in negative emotionality (0.2%), thin-ideal internalization (0.2%), dietary restraint (0.2%), modeling of pathological eating (0.2%), and BMI (0.2%). Missing data of risk factors were treated with listwise deletion technique, which resulted in omitting data for four participants. Moreover, 0.6% of the participants who showed an eating disorder onset missed at least one eating disorder diagnostic data. The attrition rate ranged from 1% (Wave 2) to 6% (Wave 8). We sometimes collected data from participants who skipped a previous assessment. That is, participants might not be able to come to an assessment in a specific year, but could come in a later year. This occurred with 30 participants (6%) during the follow-up period. Attrition was not significantly correlated with baseline levels of the potential risk factors examined in this report.

Results

PRELIMINARY ANALYSES

Among 492 participants with complete data, 11 participants already had a threshold/subthreshold eating disorder at baseline, and were thus excluded from analyses for the relevant disorder. That is, when a participant already had AN at baseline, for instance, her data would be excluded from the analysis predicting future AN onset, but not for other disorders, because there was no way for us to know which risk factors precipitated her baseline AN. During the 7-year follow-up, 24 of participants (4.9%) were diagnosed with AN (21 subthreshold AN, 4 threshold AN), 30 (6.1%) with BN (29 subthreshold BN, 7 threshold

Table 2
Correlation Matrix of Nine Independent Variables

Variables	2	3	4	5	6	7	8	9
1. Pressure to be thin	.286**	.529**	.579**	.297**	−.243**	−.157**	.525**	.420**
2. Thin-ideal internalization	–	.184**	.266**	.199**	−.127**	.008	.227**	.045
3. Body dissatisfaction		–	.498**	.322**	−.352**	−.176**	.320**	.519**
4. Dietary restraint			–	.198**	−.182**	−.066	.386**	.418**
5. Negative emotionality				–	−.329**	−.224**	.309**	.153**
6. Parent support					–	.243**	−.322**	−.200**
7. Peer support						–	−.012	−.143**
8. Modeling of eating pathology							–	.184**
9. BMI								–

*$p < .05$.
***$p < .001$.
** $p < .01$.

BN), 13 (2.6%) with BED (12 subthreshold BED, 3 threshold BED), and 24 (4.9%) with PD (12 subthreshold PD, 17 threshold PD). The sum of the numbers inside parentheses exceeded the total number because a few participants within each group developed a subthreshold eating disorder first, then a threshold eating disorder later, further emphasizing the importance of including subthreshold cases. In addition, 11 participants crossed over to another disorder during the follow-up.[1]

Correlation coefficients among risk factors are reported in Table 2. The highest variance inflation factor among the risk factors was 2.092, which was much smaller than the recommended cutoff of 10 (Neter et al., 1989). Therefore, the collinearity between predictor variables was not excessive.

PREDICTION OF ONSET OF EATING DISORDERS

We tested whether baseline risk factors univariately predicted future onset of each eating disorder using Cox proportional hazard models (see Table 3). For AN, only low zBMI was a significant predictor (HR = 0.4, $p < 0.001$) with a large effect ($d = 0.71$). For BN, high perceived pressure to be thin (HR = 1.8, $p < 0.001$), thin-ideal internalization (HR = 1.9, $p = 0.001$), body dissatisfaction (HR = 1.9, $p = 0.001$), negative emotionality (HR = 1.6, $p = 0.005$), modeling of eating pathology (HR = 1.7, $p = 0.001$), and low parent support (HR = 0.7, $p = 0.050$) were significant predictors, with medium to large effect sizes ($ds = \pm 0.28$–0.50). For BED, high perceived pressure to be thin (HR = 2.0, $p = 0.002$), thin-ideal internalization (HR = 2.3, $p = 0.006$), negative emotionality (HR = 2.1, $p = 0.004$), modeling of eating pathology (HR = 1.7, $p = 0.034$), and low parent support (HR = 0.6, $p = 0.043$) were significant predictors, with large effects ($ds = \pm 0.40$–0.65). Lastly, for PD, high perceived pressure to be thin (HR = 2.0, $p < 0.001$), body dissatisfaction (HR = 2.7, $p < 0.001$), dietary restraint (HR = 2.3, $p < 0.001$), modeling of eating pathology (HR = 1.6, $p = 0.013$), zBMI (HR = 1.8, $p = 0.007$), and low parent support (HR = 0.6, $p = 0.002$) were significant predictors, with large effects ($ds = \pm 0.37$–0.77). For the 95% confidence intervals, please refer to Table 3. Figure 1 displays a plot of ds as a function of risk factors by an eating disorder.

Because multiple risk factors simultaneously predicted BN, BED, and PD, multivariate backward stepwise logistic regressions were used to identify risk factors that showed unique predictive effects independent of the other risk factors. At each step, a risk factor with the largest insignificant p-value was dropped from a model until all remaining p-values were significant and the AIC determined the most parsimonious models. For BN, only thin-ideal internalization showed a significant unique predictive effect ($p = 0.027$), with body dissatisfaction and modeling of pathological eating showing non-significant trends ($ps = 0.072$ and 0.085, respectively) in the final model (AIC = 214.69). For BED, none of the risk factors showed significant unique predictive effects, though thin-ideal internalization and negative emotionality showed a non-significant trend ($ps = 0.099$ and 0.090, respectively) in the final model (AIC = 114.06). Lastly, for PD, body dissatisfaction and dietary restraint showed a significant unique predictive effect ($ps = 0.006$ and 0.022, respectively) in the final model (AIC = 172.04).

[1] If a baseline diagnosis predicting the later emergence of other eating disorder types was also tested, but none of the baseline diagnoses significantly predicted the later emergence of other eating disorder types.

Table 3
The Cox Proportional Hazard Models Where Development of an Eating Disorder Was Regressed Onto Baseline Risk Factors

Eating disorder	Risk factors	HR	*p*	HR 95% CI		*d*
AN (n = 24)	Pressure to be thin	0.9	0.769	0.604	1.452	−0.082
	Thin-ideal internalization	1.1	0.765	0.703	1.613	0.074
	Body dissatisfaction	0.7	0.189	0.484	1.154	−0.278
	Dietary restraint	0.7	0.135	0.445	1.113	−0.278
	Negative emotionality	1.1	0.564	0.758	1.661	0.074
	Parent support	1.5	0.140	0.881	2.465	0.316
	Peer support	1.1	0.568	0.729	1.779	0.074
	Modeling of eating pathology	1.1	0.768	0.711	1.588	0.074
	zBMI	0.4	**<0.001**	0.282	0.633	−0.714
BN (n = 30)	Pressure to be thin	1.8	**<0.001**	1.327	2.382	0.458
	Thin-ideal internalization	1.9	**0.001**	1.297	2.794	0.500
	Body dissatisfaction	1.9	**0.001**	1.296	2.707	0.500
	Dietary restraint	1.4	0.063	0.983	1.955	0.262
	Negative emotionality	1.6	**0.005**	1.159	2.260	0.366
	Parent support	0.7	**0.050**	0.534	1.000	−0.278
	Peer support	0.8	0.245	0.601	1.139	−0.174
	Modeling of eating pathology	1.7	**0.001**	1.236	2.324	0.414
	zBMI	1.3	0.191	0.881	1.892	0.205
BED (n = 13)	Pressure to be thin	2.0	**0.002**	1.295	3.065	0.540
	Thin-ideal internalization	2.3	**0.006**	1.265	4.080	0.649
	Body dissatisfaction	1.5	0.158	0.856	2.600	0.316
	Dietary restraint	1.5	0.138	0.881	2.486	0.316
	Negative emotionality	2.1	**0.004**	1.266	3.460	0.578
	Parent support	0.6	**0.043**	0.399	0.985	−0.398
	Peer support	0.7	0.074	0.443	1.038	−0.278
	Modeling of eating pathology	1.7	**0.034**	1.041	2.714	0.414
	zBMI	1.2	0.471	0.693	2.211	0.142
PD (n = 24)	Pressure to be thin	2.0	**<0.001**	1.476	2.764	0.540
	Thin-ideal internalization	1.5	0.052	0.996	2.334	0.316
	Body dissatisfaction	2.7	**<0.001**	1.785	4.226	0.774
	Dietary restraint	2.3	**<0.001**	1.588	3.448	0.649
	Negative emotionality	1.4	0.057	0.990	2.099	0.262
	Parent support	0.6	**0.001**	0.420	0.806	−0.398
	Peer support	0.9	0.596	0.617	1.319	−0.082
	Modeling of eating pathology	1.6	**0.013**	1.102	2.260	0.366
	zBMI	1.8	**0.007**	1.177	2.819	0.458

Note. AN = anorexia nervosa, BN = bulimia nervosa, BED = binge eating disorder, PD = purging disorder. HR stands for hazard ratio. Significant *p*-values are bolded ($p < .05$).

Discussion

The major objective of our study was to test whether hypothesized risk factors assessed at baseline would predict future onset of each of the four types of eating disorders over 8 years among a community sample of adolescent girls. To our knowledge, there has been no prospective study that examines whether risk factors increase the risk of future onset of each type of eating disorder in a community sample of adolescent girls. The strongest and only predictor of AN onset was low BMI in middle school. As lower-than-expected BMI as a prodromal symptom increased the risk of AN onset in the previous analysis of the same community sample (Yamamiya et al., 2022) and in Stice et al. (2021b) that examined an older, at-risk sample, results suggest that a low BMI is a core etiological factor in developmental models of AN. Analyzed data from this sample indicated that participants who later showed onset of AN exhibited a low BMI for an average of 4 years between the baseline assessment and when they eventually showed onset of AN (Stice et al., 2017, 2021b). This communicates that a low BMI in isolation is not sufficient to precipitate onset of AN. We also tested whether other cognitive risk factors showed an increase immediate before emergence of AN. Results indicated that an increase in dietary restraint, negative affect, and eating affect regulation expectancies all significantly increased in the year before emergence of AN in low BMI youths. However, there was no

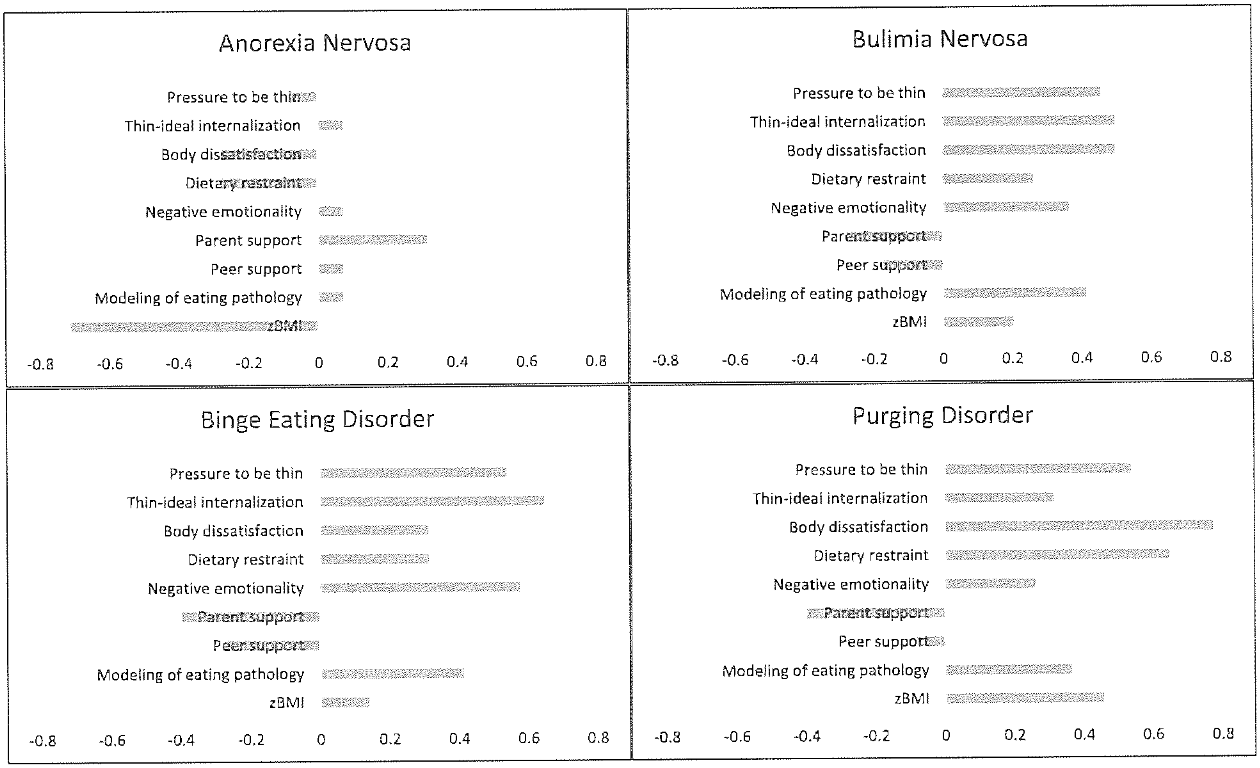

FIGURE 1 Plot of Effect Size (d) by Risk Factor by Eating Disorder. *Note*. The bar lengths represent effect sizes.

evidence that an increase in thin-ideal internalization, body dissatisfaction, or depression showed a significant increase immediately before onset of AN. This pattern of findings implies that the low BMI was not a result of elevated pressure for thinness, pursuit of the thin ideal, body dissatisfaction, or volitional dietary restriction because the low BMI develops without significant elevations of the other risk factors. Stice et al. (2022) reported the results from the receiver operator characteristic analysis using data from a large high-risk sample (N = 1,952) and revealed that having a BMI in the lowest 25% of the distribution was the optimal cut-point for predicting the future onset of AN. Our study started assessing girls at 11, so it is crucial to determine at what age the weight of those girls starts to become significantly lower than expected by monitoring girls from younger age and what precipitates the low body weight among them if not appearance-/weight-related attitudes.

Regarding BN, body dissatisfaction and negative emotionality were found to be significant predictors with medium effects, which also significantly predicted BN onset in at-risk, young women (Stice et al., 2021b). Hence, body dissatisfaction and negative emotionality may play a significant role in BN onset regardless of age groups. However, the strongest predictor among our sample was perceived pressure to be thin, which is a novel finding. The analysis of the same sample (Yamamiya et al., 2022) indicated that weight overvaluation and compensatory weight control behavior were the first prodromal symptoms emerging among girls who later developed BN. Cumulatively, these results may suggest that girls feel pressure to be thin and evaluate their body as fat, which makes them feel negative about their weight. Consequently, they may start engaging in weight-control compensatory behavior, but eventually start binge eating to counteract the strict caloric restriction, leading to recurrent binge eating accompanied by compensatory behaviors. Last, low perceived parent support as well as high modeling of eating pathology in family and friends predicted BN onset in this study. As both risk factors were also significant predictors of BED and PD, it is possible that binge eating and weight-control compensatory behavior are learned from others in girls' environment. Another possibility is that girls who feel they are not supported by their parents may try to attain their parents' affection and approval by attempting to conform to the thin beauty ideal.

As for BED, the predictors with large effects in the present study were perceived pressure to be thin, thin-ideal internalization, and negative emo-

tionality. Thin-ideal internalization and negative emotionality were also found to be the strongest predictors of BED in Stice et al. (2021b). In addition, we found the low perceived parent support to be a significant predictor of BED with a medium effect. As the number of BED onset was relatively low ($n = 13$), however, findings should be interpreted with caution. Results suggest that in addition to weight-related beliefs or attitudes influenced by sociocultural emphasis on thinness, interpersonal issues within family may induce negative emotions, which may trigger binge eating. As mentioned above, low perceived parent support and high negative emotionality also predicted future onset of BN. Therefore, recurrent episodes of binge eating may serve to buffer negative emotions associated with perceived lack of support from parents among girls who later develop BN and BED. Indeed, a clinical study of BN patients that utilized an experience sampling design has indicated that momentary negative affect predicts craving and negative urgency, which, in turn, predicts binge eating (Leenaerts et al., 2023).

Last, the strongest predictors of PD onset were body dissatisfaction and dietary restraint followed by high BMI and perceived pressure to be thin, which is similar to Stice et al.'s (2021b) study, which found body dissatisfaction and dietary restraint as the most potent predictors. However, an interesting finding of our study is that thin-ideal internalization did not predict onset of PD. Hence, though body dissatisfaction and dietary restraint may be potent risk factors that predict future onset of PD regardless of age groups, they may not be rooted in pursuit of the thin beauty ideal in adolescent girls. What triggers body dissatisfaction and motivates dieting behavior among girls who develop PD needs to be further investigated with a larger sample. Moreover, it is noteworthy that dietary restraint only predicted onset of PD among our community sample of adolescent girls, but not in an older high-risk sample (Stice et al., 2017). Thus, how dietary restraint and eating disorders are related across age groups needs further investigation as well. In sum, we have noted some similarities and differences in the present results compared to the only other studies that tested baseline risk factors predicting future onset of AN, BN, BED, and PD, involving a high-risk sample (Stice et al., 2017, 2021b). Nevertheless, the risk factors in our paper differ from those in the previous papers. Moreover, we identified different risk factors in our current paper because the baseline assessment occurred about 4 years earlier than the baseline assessment in the 2017 and 2021 reports. We likely detected fewer risk factors than some other past longitudinal studies because the baseline assessment occurred before the risk factors exhibited normative developmental increases (see Rohde et al., 2015).

Exploratory analyses of multivariate effects of risk factors revealed some notable findings as well. Among six risk factors that univariately predicted BN, only internalization of the sociocultural thin-ideal showed a unique predictive effect for future BN onset. Moreover, among six risk factors that univariately predicted PD, only body dissatisfaction and dietary restraint showed unique significant predictive effects for future PD onset. As these risk factors are also most potent predictors of the disorders, targeting them may be able to specifically prevent future BN and PD onsets. On the contrary, none of five risk factors with univariate predictive effects showed significant unique predictive relation to BED. This finding may imply that risk factors of eating disorders especially BED operate in a mediational fashion (e.g., pressure for thinness might cause internalization of the thin ideal, which prompts body dissatisfaction). Previous analyses of data from this sample have provided support for the dual pathway model for youth who later showed onset of BN, BED, or PD (Stice & van Ryzin, 2019), which posits that elevated pressure for thinness and pursuit of this beauty ideal increases risk for subsequent body dissatisfaction, which increases risk for dieting and negative affect, which increases risk for emergence of these eating disorders. It would be useful for additional prospective risk factors studies to evaluate mediational etiologic models for specific eating disorders.

In sum, our findings are compatible with etiological models of eating disorders, such as the dual pathway model (Stice & van Ryzin, 2019), described above. Our study showed that community-recruited adolescent girls who perceived pressure to achieve the sociocultural thin-ideal, internalized the thin-ideal, and/or were dissatisfied with their current weight were found to develop BN, BED, or PD. Another meaningful finding is that negative emotionality consistently predicts eating disorders in a community sample of adolescent girls and young women (Stice et al., 2021b), implying that females who later develop an eating disorder may engage in binge eating and/or weight-control compensatory behaviors in response to negative emotions, as suggested in the dual pathway model. This finding is also consistent with the emotional dysregulation model of BN (Lavender et al., 2016). In addition, low levels of perceived parent support predict eating disorders characterized by binge eating and/or

purging behavior in the present sample. As psychosocial impairment in interpersonal functioning was found to predict BED and PD in Stice et al. (2021b), behavioral eating-disorder symptoms may serve as an emotional catharsis for interpersonal issues, supporting the interpersonal difficulty model of eating disorders (Arcelus et al., 2013). Hence, the potent risk factors found in the present study should be incorporated into multifactorial etiological models of eating disorders, while tailoring the models for different age groups and/or eating-disorder types. Moreover, it might be useful for prevention programs to incorporate certain emotional factors and interpersonal issues in addition to focusing on reducing pressures for thinness.

There are some limitations of the present study. First, as all participants were recruited from one state and female, the findings may not be generalizable to those from a different region or males. Second, the number of participants who developed BED was rather small, which might increase the risk of false negative findings. Indeed, a few small to medium effects did not reach statistical significance. That is, while we had sufficient power to detect small effects for risk factors that predicted future onset of AN, BN, and PD, we had less power to detect predictors of BED onset. Third, as we tested 36 inferential tests with an alpha-level of 0.05, it is possible that a few effects we observed might have occurred by chance. However, as noted above, we had limited power due to small numbers of diagnoses in each eating-disorder group. Therefore, making Type II errors (i.e., false negative findings) is more likely than making Type I errors (i.e., false positive findings) with our dataset. Because of the relatively low sensitivity of our dataset, we decided not to use a more conservative alpha level that would further reduce sensitivity. When the Benjamini-Hochberg correction was applied to control the false discovery rate, most significant effects remained, though three significant effects became marginal (i.e., *p*-values of modeling of pathological eating to predict BED changed from 0.034 to 0.077, perceived parent support to predict BN and BED changed from 0.050 to 0.098 and from 0.043 to 0.091, respectively). Despite the limitations, our data are still valuable because a prospective study using a community sample of adolescent girls assessed over 8 years is novel and rare. In addition, we collected data across adolescence, which is a developmental period in which eating disorders typically emerge. Nevertheless, it would be useful if other independent research teams can collect similar data from a larger sample and attempt to replicate the results reported herein.

Our findings suggest that some personal factors, such as low social support and modeling of eating pathology, in addition to weight-oriented cognitions and attitudes, may increase risk for eating disorders. Therefore, these risk factors may be incorporated into existing multifactorial etiological models of eating disorders (e.g., the dual pathway model), though the models may need to be adjusted for different disorders, age groups, and current risk levels. However, most of established risk factors have predicted BN, BED, and/or PD but not AN, and we found only low BMI predicted AN in our sample. It is possible that some risk factors have been omitted in relevant studies, so we need to explore a wider range of potential risk factors to predict AN onset, particularly among adolescent girls, because AN typically develops during adolescence. In addition, we call for future research to incorporate biological risk factors, such as individual differences in reward region and inhibitory region responsivity in the brain, as well as the gut microbiome. Moreover, considering the high comorbidity of eating disorders with major depression (e.g., Becker et al., 2014), it may be imperative to investigate risk factors that uniquely predict comorbid cases.

With regard to prevention implications, our study suggests that we may need to focus on different risk factors to prevent certain eating disorders. For instance, perceived pressure to be thin and thin-ideal internalization predicted eating disorders in our study. Young girls often perceive such pressure from peers, family, and the media, which frequently glorify and promote the thin ideal in society (Stice, 1998, 2001). The results provide support for prevention programs that seek to reduce pursuit of the thin beauty ideal (the Body Project). Randomized trials have confirmed that reducing pursuit of the thin ideal effectively reduces future onset of eating disorders (Stice et al., 2021a). The present results identify several novel risk factors, such as low social support and modeling of eating disordered behaviors, which predicted eating disorders involving binge eating and/or purging behaviors in our study. Hence, it is possible that eating disorders are related to certain environmental factors that could be targeted in prevention programs. It would be useful to test whether increasing social support, for example, reduces future onset of eating disorders in randomized trials. The present findings also imply that it would be important to test whether prevention programs reduce risk for future onset of each eating disorder type. For instance, a recent study found that the Body Project does not reduce risk for future onset of AN or BED (D'Adamo et al.,

2023), which suggests that there might be value in creating prevention programs that seek to reduce transdiagnostic risk factors that predict onset of all eating disorders. Therefore, it may be necessary to create distinct prevention programs for the various eating disorders if there are few transdiagnostic risk factors.

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EMPIRICAL ARTICLE

Development and Predictive Effects of Eating Disorder Risk Factors During Adolescence: Implications for Prevention Efforts

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ABSTRACT

Objective: Although several prospective studies have identified factors that increase risk for eating disorders, little is known about when these risk factors emerge and escalate, or when they begin to predict future eating disorder onset. The objective of this report was to address these key research gaps.

Method: Data were examined from a prospective study of 496 community female adolescents ($M = 13.5$, $SD = 0.7$ at baseline) who completed eight annual assessments of potential risk factors and eating disorders from preadolescence to young adulthood.

Results: Three variables exhibited positive linear increases: Perceived pressure to be thin, thin-ideal internalization, and body dissatisfaction; three were best characterized as quadratic effects: dieting (essentially little change); negative affectivity (overall decrease), and BMI (overall increase). Elevated body dissatisfaction at ages 13, 14, 15, and 16 predicted DSM-5 eating disorders onset in the 4-year period after each assessment, but the predictive effects of other risk factors were largely confined to age 14; BMI did not predict eating disorders at any age.

Discussion: The results imply that these risk factors are present by early adolescence, although eating disorders tend to emerge in late adolescence and early adulthood. These findings emphasize the need for efficacious eating disorder prevention programs for early adolescent girls, perhaps targeting 14-year olds, when risk factors seem to be most predictive. In early adolescence, it might be fruitful to target girls with body dissatisfaction, as this was the most consistent predictor of early eating disorder onset in this study. © 2014 Wiley Periodicals, Inc.

Keywords: eating disorders; adolescence; developmental course; predictive effects; body dissatisfaction

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Introduction

Eating disorders show a chronic course and result in significant functional impairment, emotional distress, and medical problems.[1–3] A cross-sectional retrospective epidemiological study suggested that approximately 7.5% of young women meet criteria for a DSM-IV-TR[4] eating disorder of anorexia nervosa, bulimia nervosa, or binge eating disorder (BED).[1] A recent examination of the natural history of DSM-5 eating disorders[5] in a community sample of 496 female adolescents who completed annual diagnostic interviews over an 8-year period found that 13% of participants experienced some form of threshold or subthreshold eating disorder by age 20, with the peak age of onset for bulimia nervosa and BED being 17–18 years of age and 18–20 for purging disorder.[6] Retrospective data suggest a median age of onset (with interquartile range) of 18 years (16–22) for anorexia nervosa, 18 years (14–22) for bulimia nervosa, and 21 years (17–32) for BED among community-recruited adults.[1]

Although the incidence of eating disorders in early adolescence (ages 10–14) is very low,[3,7] extant data suggest that risk factors for symptoms of eating disorders[8] and eating disorder syndromes[7,9] escalate in early adolescence. Accordingly, the focus of the present report is on the development and predictive power of potential eating disorder risk factors during early adolescence. The first aim of this study was to describe the developmental changes in potential risk factors from age 13 to 21, using data from an 8-year longitudinal study of community female adolescents.[6] We focused on young women because they are at much higher

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risk for onset of eating pathology than young men.[1] We examine whether the course of each variable is increasing, decreasing, or stable over this developmental period and, if change is present, whether it is linear or quadratic, as nonlinear change might capture critical periods of increases in risk factors. These data should provide direction regarding when to target populations at elevated risk for eating disorders by virtue of possessing these risk factors. Furthermore, if there are qualitatively distinct periods, during which different risk factors emerge before eating disorder onset, it may be possible to improve the yield of prevention efforts by targeting different risk factors during these distinct developmental periods. It is possible that decreasing these risk factors may reduce future eating disorder onset, although predictive effects cannot establish a causal relation because it is always possible that some third variable explains both the emergence of the risk factor and eating pathology.

Few studies have examined the course of potential risk factors before mid-adolescence. One exception is Bucchianeri, et al.,[10] who followed a cohort of girls recruited during middle school (*M* age at first assessment = 12.8 years, *SD* = 0.7) over a 10-year period; data revealed a significant upward linear increase in body dissatisfaction from middle school to high school and to young adulthood. However, body mass index (BMI = kg/m^2) scores also increased across all three time points for both male and female participants, and after adjusting for BMI, the linear trend in body dissatisfaction was nonsignificant. No studies, to our knowledge, have investigated the temporal development of several risk factors before and during peak period of eating disorder onset (i.e., from early adolescence to young adulthood).

Guided by the dual-pathway model of eating pathology[11] and prior research with female adolescents,[9,12–15] we focused on six potential risk factors: (1) perceived pressure to be thin, (2) thin-ideal internalization, (3) body dissatisfaction, (4) dieting, (5) temperamental negative affectivity (i.e., the tendency to experience negative emotional states), and (6) body mass. The dual-pathway model posits that perceived pressure to be thin from significant others and the media and internalization of the thin beauty ideal produces body dissatisfaction, which in turn promotes unhealthy dieting behaviors that may progress to an eating disorder. Body dissatisfaction may also contribute to negative affect given the importance of appearance in Western culture, which in turn might lead people to binge eat to provide comfort and distraction from negative emotions. According to the affect regulation model,[11] people binge eat in an effort to achieve comfort and distraction from their negative emotions. Previous research with adolescents has found that female adolescents in 6–9th grade reporting social pressure to be thin and body image preoccupation showed a higher risk for onset of threshold or subthreshold bulimia nervosa or binge eating disorder over 3-year follow-up,[14] high school women reporting weight and shape concerns and negative affectivity showed a higher risk for onset of threshold or subthreshold bulimia nervosa over 4-year follow-up,[8] and female adolescents (11–15 years of age) reporting elevated dietary restraint showed elevated risk for onset of threshold or subthreshold bulimia nervosa over 5-year follow-up.[16] It is arguably more important to identify youth at elevated risk for *any* eating disorder because prevention programs should ideally target all eating disorders, rather than just one type of eating disorder, and elevated dietary restraint has been found to increase risk for onset of any eating disorder among young women (16–23 years of age) over 2-year follow-up,[12] young women (14–15 years of age) over 3-year follow-up,[14] and 16-year-old women over 1-year follow-up.[15] In an earlier report examining data used in the present study using classification tree analysis to predict onset of threshold and subthreshold eating disorders over 8-year follow-up,[17] a three-way interaction emerged suggesting a body dissatisfaction pathway to eating disorder onset that was amplified by depressive symptoms, and a pathway characterized by self-reported dieting among young women who are more satisfied with their bodies. Furthermore, increased adiposity has been theorized to result in both increased social pressure to be thin and body dissatisfaction, which putatively lead to dieting, negative affect, and elevated risk for eating pathology.[18] BMI is known to increase during the adolescent developmental period.[19] For example, one study found that self-reported BMI among female adolescents in their younger cohort increased from an average of 21.7 at the first assessment (*M* age = 12.8) to an average of 26.4 at the third assessment (*M* age = 23.2).[10]

To identify variables that predict pathological eating behavior in children and early adolescents, Gardner et al.[20] examined the degree, to which six variables (weight, teasing, body esteem, body dissatisfaction, depression, perceived body size, ideal body size) predicted elevated scores on an eating disorder survey in 216 female and male children ages 6–14 who were assessed annually for 3 years. They examined each predictor at various ages to identify when the factors tended to became

significant predictors of elevated eating disorder scores, finding that low body esteem became a significant factor at age 9, depression at age 10, body dissatisfaction and larger perceived body size judgments at age 11, and thinner ideal body sizes at age 12. Using a similar analytic approach, our second aim was to examine whether each of the Aim 1 potential risk factors examined during early adolescence predicted subsequent onset of DSM-5 eating disorders, and whether the predictive effects of these risk factors varied as a function of age. We sought to extend the findings of Gardner et al.[20] by (a) following a larger cohort of youth, (b) examining a longer period of time, and (c) by predicting onset of DSM-5 eating disorders as determined by diagnostic interview. To address this aim, we examined the degree, to which each of the six potential risk factors at ages 13, 14, 15, and 16 significantly predicted the onset of eating disorders in the 4-year period following each assessment. These data may also advance etiologic models for eating disorders by illuminating the earliest risk factors that predict eating disorder onset.

Method

Participants and Procedures

Participants were 496 female adolescents recruited from public ($n = 409$) and private middle schools ($n = 87$) in a large US city. Participants ranged from 12 to 15 years of age ($M = 13.5$, $SD = 0.7$) and were in 7th or 8th grade at T1. The sample was composed of 2% Asian/Pacific Islanders, 7% African Americans, 68% Caucasians, 18% Hispanics, 1% Native Americans, and 4% other/mixed, which is generally representative of the ethnic composition of the schools, from which we sampled (2% Asian/Pacific Islanders; 8% African Americans, 65% Caucasians, 21% Hispanics; 4% "other or mixed").[6,11] Average parental education, a proxy for socioeconomic status, was 29% high school graduate or less, 23% some college, 33% college graduate, and 15% graduate degree, which was representative of the metropolitan area, from which we sampled (34% high school graduate or less; 25% some college; 26% college graduate; 15% graduate degree).[6,11]

The study was described as an investigation of adolescent mental and physical health. An informed consent letter and self-addressed return envelope were sent to parents of middle school students, resulting in a baseline participation rate of 56%, echoing recruitment rates observed in other similar longitudinal studies involving repeated diagnostic interviews.[3] Participants completed a survey and an interview at baseline (T1) and at seven annual follow-ups (T2, T3, T4, T5, T6, T7, and T8). Trained female assessors conducted diagnostic interviews. Assessors had to demonstrate an inter-rater agreement ($k > 0.80$) with the project manager using tape-recorded interviews before collecting data. Assessments took place at the school, the participants' place of residence, or the research office. Participants received a gift certificate or cash payment for completing each assessment. The University of Texas at Austin Institutional Review Board approved this study.

Measures

Perceived sociocultural pressure to be thin from family, friends, dating partners, and the media was assessed with the Perceived Sociocultural Pressure Scale.[21] Response options to these 10 items (e.g., "I've felt pressure from my friends to lose weight") ranged from 1 to 5 (1 = *none*, 3 = *some*, 5 = *a lot*). Items for this scale (and those below) were averaged for scoring. This scale has shown internal consistency ($\alpha = .88$), 2-week test-retest reliability ($r = 0.93$), and predictive validity for future onset of bulimic symptoms ($\alpha = 0.85$ at T1).[21]

Thin-ideal internalization was assessed with the Ideal-Body Stereotype Scale-Revised,[22] which assesses agreement with statements concerning what attractive women look like. Response options to these six items (e.g., "Slender women are more attractive") were: 1 = *strongly disagree*, 2= *disagree*, 3 = *neutral*, 4 = *agree*, 5 = *strongly agree*. This scale has shown internal consistency ($\alpha = 0.89$), 2-week test-retest reliability ($r = 0.80$), sensitivity to detecting effects of an eating disorder prevention program that focuses on reducing thin-ideal internalization, and predictive validity for future bulimic symptom onset ($\alpha = 0.81$ at T1).[22]

Body dissatisfaction was assessed with nine items from the Satisfaction and Dissatisfaction with Body Parts Scale[23] that measured satisfaction with body parts that are often of concern to girls and women (e.g., waist, thighs). Response options were: 1 = *extremely dissatisfied*, 2 = *moderately dissatisfied*, 3 = *neutral*, 4 = *moderately satisfied*, 5 = *extremely satisfied*. This scale has shown internal consistency ($\alpha = 0.94$), 3-week test-retest reliability ($r = 0.90$), sensitivity to detecting effects from an eating disorder prevention program, and predictive validity for future onset of eating disorders ($\alpha = 0.94$ at T1).[22]

Dieting was assessed with the Dutch Restrained Eating Scale[24] that measures the frequency of dieting behaviors. Response options to these nine items (e.g., "If you have put on weight, do you eat less than you normally would?") were: 1 = *never*, 2 = *seldom*, 3 = *sometimes*, 4 = *often*, 5 = *always*. This scale has shown internal consistency ($\alpha = 0.95$), 2-week test-retest reliability ($r = 0.82$), sensitivity to detecting effects of eating disorder prevention programs, and predictive validity for future onset of eating disorders ($\alpha = 0.91$ at T1).[24]

Negative affectivity was assessed with Buss and Plomin's Emotionality Scale,[25] which measures agreement with statements regarding tendencies to become affectively distressed. Using a response format modified from the original scale, participants indicated how much they agreed with eight items regarding their tendency to become emotionally distressed or aroused (e.g., "I frequently get upset") using the following response options: 1 = *strongly disagree*, 2 = *disagree*, 3 = *neutral*, 4 = *agree*, 5 = *strongly agree*. This scale showed internal consistency ($\alpha = 0.80$ at T1), convergent validity with other measures of negative affect[25] and predictive validity for future increases in bulimic symptoms.[11]

Body mass was determined by the body mass index (BMI = kg/m2), which was obtained by physical measurements. Height was measured to the nearest millimeter using portable stadiometers. Weight was assessed to the nearest 0.1 kg using digital scales with participants wearing light indoor clothing without shoes or coats. Height and weight were measured twice each and averaged. Height and weight were directly assessed in the 3,324 diagnostic interviews conducted in person, but were based on self-report for the 534 diagnostic interviews conducted over the phone because subjects had moved from the Austin area (13.8% of all interviews).

Eating pathology was assessed by the Eating Disorders Diagnostic Interview (EDDI), which probed for eating disorder symptoms over the past 12-months at each assessment.[17] The EDDI is a semi-structured interview that was adapted from the Eating Disorder Examination (EDE)[26] by inquiring about the presence of each eating disorder symptom on a monthly basis over the past year and by omitting nondiagnostic items from the weight concerns, shape concerns, eating concerns, and dietary restraint subscales. We used these data to determine whether participants met criteria for the proposed DSM-5 eating disorders.[6] Specifically, we diagnosed the following DSM-5 disorders: anorexia nervosa, bulimia nervosa, BED, and other specified feeding or eating disorder (which includes atypical anorexia nervosa, bulimia nervosa of low frequency or limited duration, BED of low frequency or limited duration, and purging disorder; a description of the operationalizations of subthreshold conditions described previously[6]). Test-retest reliability was assessed by randomly selecting a subset of 184 participants who were interviewed by the assessors and then re-interviewed by the same assessor within a week; the test-retest reliability was $K = 0.79$ for DSM-5 eating disorders. Inter-rater agreement for the eating disorder diagnoses was assessed by randomly selecting subset of 207 participants who were re-interviewed by a second blinded assessor; the inter-rater agreement was $K = 0.75$ for DSM-5 eating disorders. In support of the validity of the EDDI, participants with versus without DSM-5 eating disorders (both threshold disorders and "other specified feeding or eating disorders") report elevated functional impairment, emotional distress, suicidal ideation, and mental health treatment, and abnormalities in body mass[6] and the EDDI has been shown to detect effects of eating disorder prevention programs.[22]

Statistical Methods

We investigated the first aim by fitting linear and quadratic relations wherein each of the six potential risk factors was regressed on the participant's age for linear models and regressed on age and quadratic age for the quadratic models. Before the analysis, age and quadratic age were centered at age 13, so that the intercept represents the estimated level of the outcome at age 13. All models were fit using mixed models implemented with nlme package from the R project.[27] We linked the T1–T8 assessments to the participant's closest age because we were interested in developmental changes in risk factors based on participant age, rather than the assessment wave. Effect sizes were estimated by converting *t* values to Pearson's *r*. We quantified the change in each risk factor using the change in the marginal means between age 13 and 21 divided by age 13 standard deviation, which represents the change in standard deviations.

We investigated the second aim using logistic regression models implemented using the glm function from the R Project.[28] The dependent variable was first incidence of any DSM-5 eating disorder (ED) reported within 4 years following each respective assessment, henceforth referred to as adolescent eating disorder onset, which permitted us to compare the predictive power of potential risk factors each year of early adolescence (participants diagnosed with an eating disorder in the same assessment or before the assessment point were excluded from the analysis, and participants diagnosed with an eating disorder more than 4 years following that particular assessment). Adolescent eating disorder onset was regressed on each of the potential risk factors measured at ages 13, 14, 15, and 16 (number of eating disorder onset cases for each period were 25, 25, 31, and 39, respectively); six participants had an eating disorder at or before age 13 and were not included in the Aim 2 analyses. Potential risk factors were transformed to *z* scores within age before model fitting to facilitate the interpretation of odds ratios: odds ratio thus represent a one standard deviation change in the independent variables.

We implemented multiple imputation for Aim 2 so models at each of the four ages, at which the risk factors were assessed included all participants. For the models examining body mass, we used an age-standardized BMI (i.e., the number of standard deviations ± the BMI for a putative age). Missing data values were imputed using the Amelia II package developed for the R project, which uses available data to impute missing values via a

TABLE 1. Linear and quadratic models of change in risk factors between age 13 and 21

Outcome and Model	Parameter	Estimate	Standard Error	t	p	r
Perceived pressure to be thin						
Linear	Intercept	1.75	0.03	51.90	<.001	.92
	Linear	0.05	0.00	10.49	<.001	.43
Quadratic	Intercept	1.76	0.04	43.93	<.001	.90
	Linear	0.04	0.02	2.74	.006	.12
	Quadratic	1.75	0.03	51.90	<.001	.92
Thin-ideal internalization						
Linear	Intercept	3.22	0.03	112.87	<.001	.98
	Linear	0.02	0.00	6.71	<.001	.29
Quadratic	Intercept	3.21	0.03	96.95	<.001	.98
	Linear	0.03	0.01	2.63	.009	.12
	Quadratic	0.00	0.00	−0.77	.440	−.04
Body dissatisfaction						
Linear	Intercept	2.78	0.04	74.69	<.001	.96
	Linear	0.02	0.00	4.97	<.001	.22
Quadratic	Intercept	2.75	0.04	65.24	<.001	.95
	Linear	0.04	0.02	2.74	.006	.12
	Quadratic	0.00	0.00	−1.40	.161	−.06
Dieting						
Linear	Intercept	2.11	0.03	60.94	<.001	.94
	Linear	0.00	0.00	0.55	.583	.03
Quadratic	Intercept	2.17	0.04	53.67	<.001	.93
	Linear	−0.04	0.02	−2.66	.008	−.12
	Quadratic	0.01	0.00	2.94	.003	.13
Negative affectivity						
Linear	Intercept	2.82	0.03	91.39	<.001	.97
	Linear	−0.03	0.01	−5.01	<.001	−.22
Quadratic	Intercept	2.80	0.04	77.28	<.001	.96
	Linear	−0.01	0.02	−0.69	.490	−.03
	Quadratic	0.00	0.00	−0.83	.406	−.04
Body mass index						
Linear	Intercept	21.16	0.22	97.12	<.001	.98
	Linear	0.35	0.01	29.35	<.001	.80
Quadratic	Intercept	20.86	0.22	92.93	<.001	.97
	Linear	0.58	0.04	13.74	<.001	.53
	Quadratic	−0.03	0.01	−5.63	<.001	−.25

bootstrapping approach. The observed and imputed data were compared to ensure that imputed values were in the same range as observed data. Missing data were replaced with imputed values in 20 data sets and each data set was analyzed separately; model parameters and standard errors from models fit to each of the twenty data sets were combined for the final results.

Results

Preliminary Analyses

With respect to attrition, the percentages of participants missing self-report and diagnostic interview data from were 0% ($N = 496$), 1% ($N = 491$), 3% ($N = 481$), 3% ($N = 481$), 2% ($N = 486$), 3% ($N = 481$), 4% ($N = 476$), and 6% ($N = 466$) for each of the eight annual assessments. We were often able to collect data from participants who did not provide data at an earlier assessment (99% of participants provided data at baseline and at least one additional assessment). Attrition was not significantly correlated with any of the potential risk factor variables or with eating disorder diagnosis.

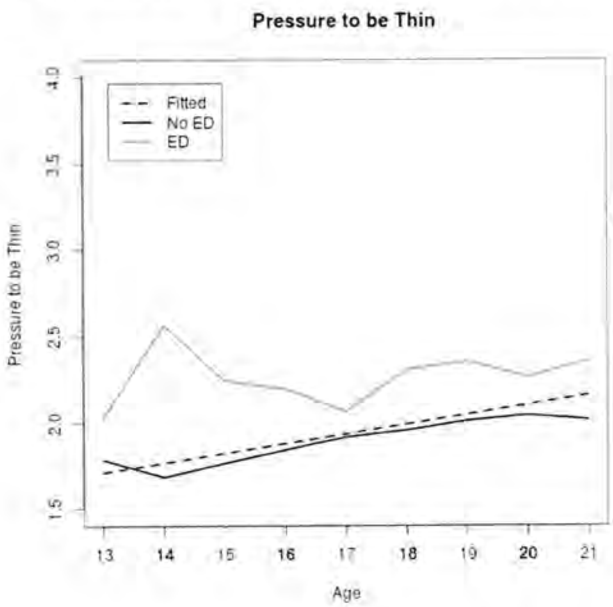
Regarding the incidence of DSM-5 eating disorders between ages 14–20, a total of 59 participants (12.0%) experienced at least one eating disorder (atypical AN $n = 12$, anorexia nervosa $n = 3$, subthreshold bulimia nervosa $n = 21$, bulimia nervosa $n = 12$, subthreshold BED $n = 14$, BED $n = 14$, purging disorder $n = 17$; 33 participants had more than one disorder).

Developmental Course of Potential Risk Factors From Ages 13 to 21

Results for Aim 1 models are presented in **Table 1**. Three of the potential risk factors exhibited positive linear increases across the age range, but did not exhibit a quadratic effect: Perceived pressure to be thin [$t(2771) = 10.49$, $p < .001$], thin-ideal internalization [$t(3248) = 6.71$, $p < .001$], and body dissatisfaction [$t(3248) = 4.97$, $p < .001$]. Dieting exhibited a significant negative linear effect [$t(3246) = -2.66$, $p = .008$], indicating an instantaneous decrease at the intercept, and a significant positive quadratic effect [$t(3246) = 2.94$, $p = .003$], indicating an increasingly positive increase in dieting across time. Negative affectivity exhibited a significant linear

decrease across time [$t(2353) = -5.01$, $p < .001$]. BMI exhibited a significant positive linear effect [$t(3246) = -13.74$, $p < .001$], indicating an instantaneous increase at the intercept, and a significant negative quadratic effect [$t(3246) = -5.63$, $p < .001$] indicating that the positive increase in BMI decelerated across time. **Figure 1** through **Figure 6** plot the fitted lines showing linear or quadratic effects for average levels of the potential risk factors for the full sample, and the observed average levels for participants who remain free of an eating disorder and those who exhibited eating disorder onset at age 16 or later. Perceived pressure to be thin exhibited a 0.49 standard deviation increase between 13 and 21; thin-ideal internalization exhibited a 0.27 standard deviations increase between 13 and 21; body dissatisfaction exhibited a 0.17 standard deviations increase between 13 and 21; dieting exhibited a 0.03 standard deviations increase between 13 and 21; negative affectivity exhibited a 0.37 standard deviations decrease between 13 and 21; and BMI exhibited a 0.61 standard deviations increase between 13 and 21.

FIGURE 1. Perceived pressure to be thin: Fitted linear effects for full sample and observed levels for noneating disordered participants and participants exhibiting eating disorders.



Degree to Which Risk Factors at 13–16 Predict Future Eating Disorder Onset

Results for Aim 2 models are presented in **Table 2**. Five of the six variables were significant predictors of subsequent eating disorder onset at one or more of the early adolescent timepoints, although the variables differed markedly in their degree of significance. One risk factor – body dissatisfaction – significantly predicted future eating disorders at all four of the examined assessment points. A second variable – negative affectivity –significantly predicted eating disorder onset at two of the four assessment points (ages 14 and 15), and three risk factors – perceived pressure to be thin, thin-ideal internalization, and dieting – predicted eating disorder onset at only one of the four early adolescent assessment points (age 14). Body mass

TABLE 2. Logistic regression analyses predicting incidence of eating disorders (within the subsequent 4 years) for risk factors assessed at ages 13, 14, 15, and 16

Risk Factor	Age	Coefficient	*SE*	*df*	*t*	*p*	Odds Ratio	95% CI
Perceived pressure to be thin	13	0.47	0.24	113	1.94	.055	1.60	0.99–2.56
	14	0.76	0.21	254	3.60	<.001	2.14	1.40–3.22
	15	0.28	0.22	120	1.27	.207	1.33	0.85–2.08
	16	0.17	0.16	460	1.02	.309	1.18	0.86–1.63
Thin-ideal internalization	13	0.35	0.31	56	1.15	.257	1.43	0.76–2.66
	14	0.71	0.25	297	2.88	.004	2.04	1.25–3.32
	15	0.01	0.19	369	0.06	.950	1.01	0.69–1.48
	16	0.03	0.17	449	0.16	.873	1.03	0.73–1.43
Body dissatisfaction	13	0.52	0.25	118	2.03	.044	1.68	1.01–2.77
	14	0.64	0.23	402	2.79	.005	1.89	1.21–2.97
	15	0.41	0.21	325	1.99	.048	1.51	1.00–2.25
	16	0.51	0.17	457	2.93	.004	1.67	1.19–2.34
Dieting	13	0.46	0.25	107	1.82	.072	1.59	0.96–2.61
	14	0.65	0.20	364	3.29	.001	1.92	1.30–2.83
	15	0.10	0.19	394	0.54	.593	1.11	0.76–1.62
	16	0.21	0.16	459	1.28	.200	1.23	0.90–1.70
Negative affectivity	13	0.38	0.28	71	1.38	.172	1.46	0.84–2.53
	14	0.65	0.22	356	3.01	.003	1.91	1.25–2.92
	15	0.67	0.19	376	3.58	<.001	1.96	1.35–2.83
	16	0.28	0.16	463	1.72	.087	1.32	0.96–1.82
Body mass index	13	0.15	0.30	49	0.48	.631	1.16	0.63–2.12
	14	0.08	0.20	384	0.40	.689	1.08	0.73–1.60
	15	0.18	0.18	346	1.01	.314	1.20	0.84–1.70
	16	0.13	0.15	444	0.85	.394	1.14	0.84–1.52

FIGURE 2. Thin-ideal internalization: Fitted linear effects for full sample and observed levels for noneating disordered participants and participants exhibiting eating disorders.

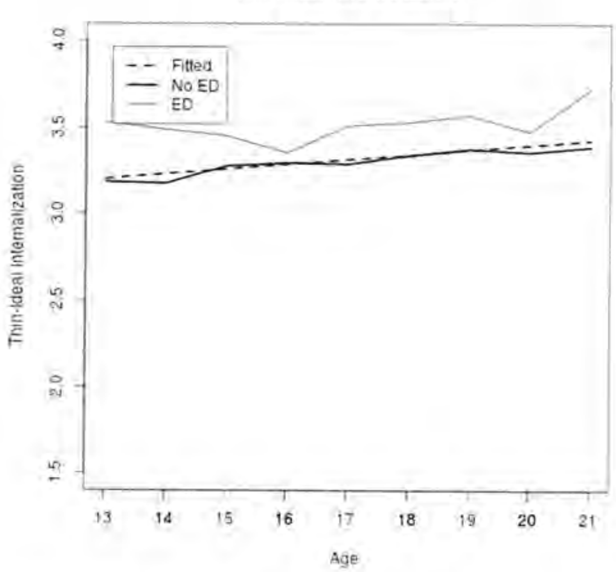
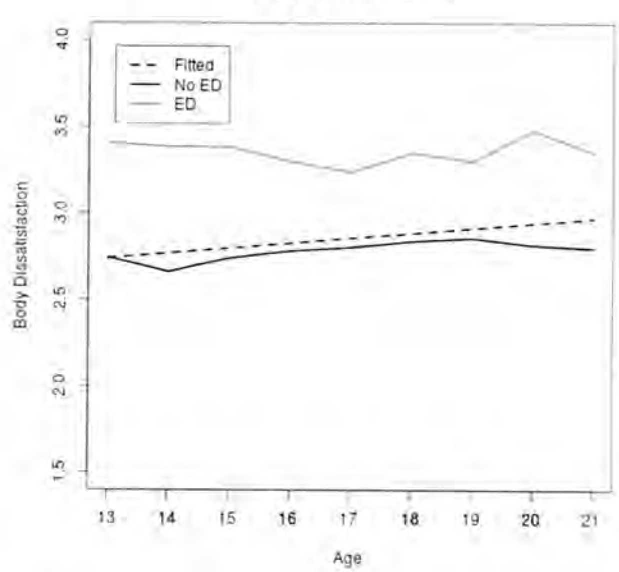


FIGURE 3. Body dissatisfaction: Fitted linear effects for full sample and observed levels for noneating disordered participants and participants exhibiting eating disorders.



index failed to predict eating disorder onset at any of the four examined age points.

Another method of summarizing the Aim 2 results involves the number of predictive effects at each age. With this focus, the greatest number of risk factors were significant at the age 14 assessment; five of six measures at that time point significantly predicted eating disorder onset within the next four years. Conversely, only one variable was significant at age 13 and two were significant at age 15.

Discussion

The goals of this study were to describe developmental changes in the levels of six potential risk factors for eating disorder onset from ages 13 to 21 and to examine whether the presence of each risk factor at ages 13–16 significantly predicted the first incidence of eating disorders within the 4 years following that assessment point. We focused on the following six potential risk factors: perceived pressure to be thin, thin-ideal internalization, body dissatisfaction, dieting, negative affectivity, and body mass.

Regarding the development of potential risk factors during this critical and complex developmental period, three of the six variables exhibited a positive linear increase, two exhibited a positive quadratic increase, and one a negative linear decrease. Of the three variables that significantly increased in a linear fashion – perceived pressure to be thin, thin-ideal internalization, and body dissatisfaction – the first variable (perceived pressure to be thin) appeared to have the largest increase over time; thin-ideal internalization and body dissatisfaction had statistically significant increases, but these changes both reflected only slight increases over an 8-year period. Self-reported dieting was most appropriately characterized as a quadratic line, first decreasing slightly and then increasing from 13 to 21 years of age, appearing to exhibit the least change over 8 years. BMI was also most appropriately charted as a quadratic line, first increasing markedly and then decelerating over time, for an overall total increase. Negative affectivity was the only variable to exhibit a significant decrease from ages 13 to 21. Thus, although full-threshold eating disorders are rare in early adolescence, inspection of fitted lines in Figures 1–6 suggest that, with the exception of body mass and possibly also perceived pressure to be thin, the potential risk factors examined in this report appear to be present by age 13 and do not show marked increases from early adolescence into young adulthood. The lack of substantial change across such a long and important developmental period in the lifespan for four of the six examined risk factors is striking.

An examination of the developmental course of potential eating disorder risk factors in this degree of detail and scope has not been previously

FIGURE 4. Dieting: Fitted quadratic effects for full sample and observed levels for noneating disordered participants and participants exhibiting eating disorders.

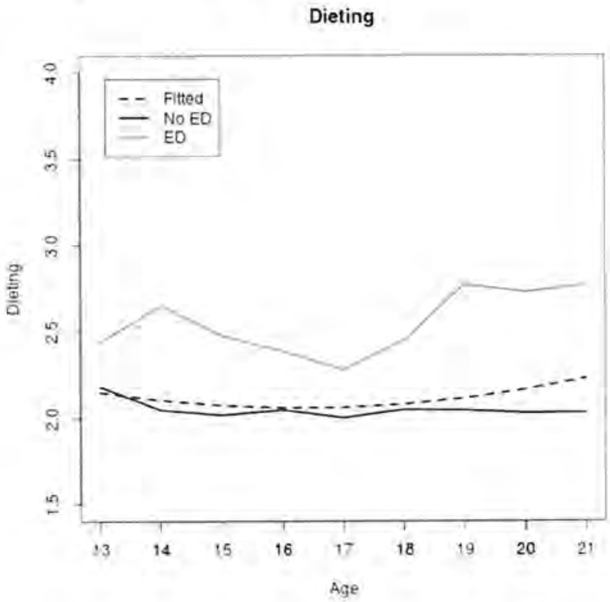
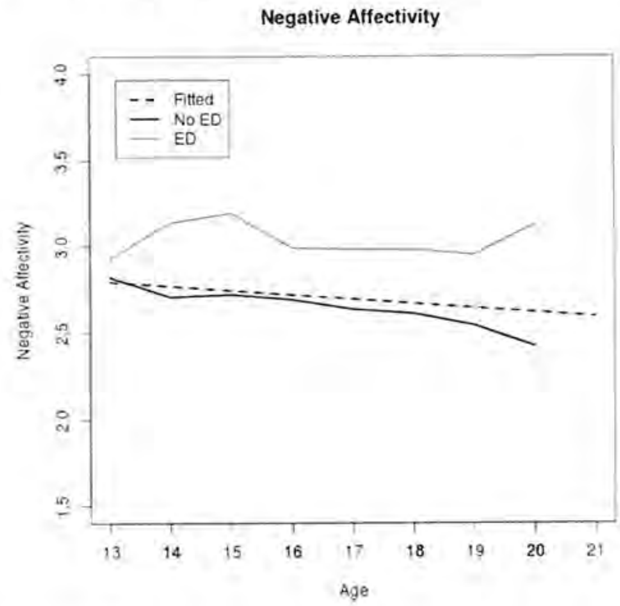
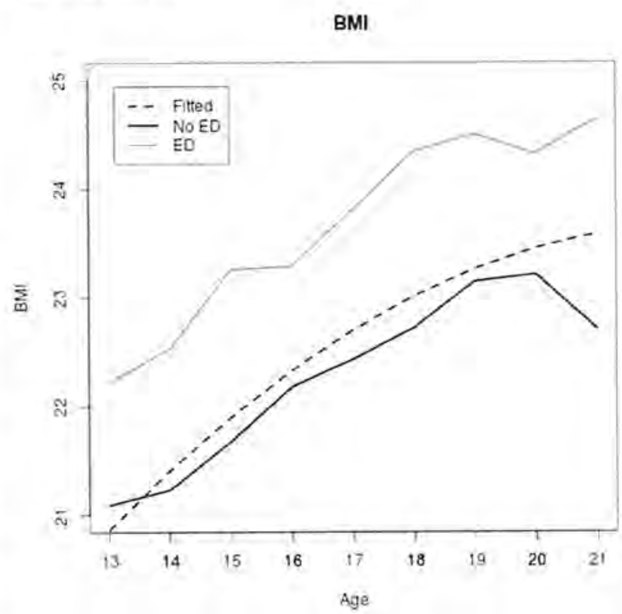


FIGURE 5. Negative affectivity: Fitted linear effects for full sample and observed levels for noneating disordered participants and participants exhibiting eating disorders.



conducted. One of the most relevant studies to examine the issue of risk factor course of development[10] reported a significant upward linear increase in body dissatisfaction from middle school to young adulthood. However, the linear trend in body dissatisfaction in that study became nonsignificant after adjusting for BMI, which also increased during this time period. We conducted a similar control by fitting the linear trend in body dissatisfaction controlling for age-standardized BMI, and found that the linear trend for body dissatisfaction remained significant [$t(3192) = 4.03$, $p < .001$] controlling for zBMI, which was treated as a time-varying covariate in the model. Thus, the increase in body dissatisfaction in our sample could not be attributed solely to changes in body composition from 13 to 21 years of age. The discrepancy between the effects reported in the present study and those reported previously by Bucchianeri et al. may have been due to greater accuracy in modeling growth in the present study (8 data points rather than 3), greater statistical power ($N = 496$ vs. 250 girls in the younger cohort with self-reported BMI), or the fact that the three assessment points in their study went further into early adulthood (*M* age at the third assessment = 23.2 years).

FIGURE 6. BMI Fitted linear effects for full sample and observed levels for noneating disordered participants and participants exhibiting eating disorders.



Overall, the results of Aim 1 imply that, though eating disorders tend to emerge in late adolescence and early adulthood, most of the examined risk factors are present by early adolescence. The pattern of results also supports the notion that a general dissatisfaction with one's body emerges before rather than after perceived increases in the pressure to attain an unrealistic version of thinness promoted for women in many Western cultures. Levels of body dissatisfaction also appeared to be elevated before significant increases in body mass

that occur in middle and late adolescence. Given that four of the six examined factors did not markedly increase after age 13 indicates the importance of longitudinal studies that track the course of these factors starting even earlier in the lifespan to better capture their emergence and developmental course.

Our second aim involved the degree, to which each of these six risk factors at ages 13, 14, 15, and 16 significantly predicted the first incidence of an eating disorder within the following 4-year period, in an effort to determine whether it would be optimal to implement prevention programs in early adolescence and, if so, which high risk populations should be targeted. Only one variable emerged as a significant predicted at age 13 (body dissatisfaction), whereas five of the six variables at age 14 significantly predicted a future eating disorder. Two risk factors at age 15 were significant predictors but only one remained significant at age 16. Of the variables we examined, body dissatisfaction was clearly the most consistent and robust predictor of future eating disorder, being significant at all four early adolescent timepoints, suggesting that it is an important high-risk population to target with prevention efforts. Elevated body dissatisfaction had a mean odds ratio of 1.68 across the four assessment points, suggesting that this risk factor increased the likelihood of developing an eating disorder by 68%. The finding that body dissatisfaction was the most consistently potent risk factor among those we examined may suggest that a general deviation from a perceived physical ideal, rather than either perceived pressure to attain unreasonable thinness or an idealization of thinness, might first motivate young female adolescents to begin engaging in unhealthy weight control behaviors that typify eating disorders, though it is not possible to draw causal inferences from such prospective effects. The overall findings also support the notion that early negative affectivity (i.e., the increased tendency to experience unpleasant emotional statues such as fear, frustration, sadness, and annoyance) functions as a significant predictor of pathological eating in young women, being significant at two of four early adolescent assessment points examined in the current study.

The present findings parallel the results from Gardner et al.,[20] who examined a younger sample, starting with girls and boys ages 6, 9, and 12, assessing them annually for 3 years. They report that low body esteem emerged as the first significant predictor of elevated eating disorder scores on a survey at age 9, followed by depression at age 10, body dissatisfaction and larger perceived body size judgments at age 11, and, finally, thinner ideal body sizes at age 12.

No support was found in the present study for elevated body mass to increase the risk for future eating disorders in young female adolescents. This variable was the only examined measure that did not predict eating disorder at any of the four assessment points. Although BMI has significantly predicted increases in eating pathology in some studies,[21] a meta-analytic review[29] suggested that, in general, research has found that elevated body mass functions as a stronger risk factor for specific eating disorder risk factors, such as perceived pressure to be thin, body dissatisfaction, and dieting than for future eating pathology per se. This overall pattern of findings may suggest that subjective body dissatisfaction, rather than elevated adiposity, might set the stage for the emergence of disordered eating behaviors.

A striking feature of results in the present study is that five risk factors were highly significant predictors at age 14, whereas only one factor attained significance at age 13. The average odds ratio for the five significant risk factors at age 14 was 1.98, indicating that these variables on average doubled the likelihood of eating disorder onset. This pattern suggests that age 14 may be a key developmental time point to intervene, perhaps due to the combination of physical and cognitive maturational processes, as female adolescents' transition from early to middle adolescence. For example, most female adolescents have completed puberty by this time, and in addition to this significant physical change experience a variety of major cognitive and interpersonal changes, including an increasing capacity for abstract thinking, a more abstract characterization of themselves, increases in the influence of peers, and the onset of dating and sexual experiences.[30]

Whereas we previously examined the onset and course of DSM-IV[2] and DSM-5[6] eating disorders during adolescence, the present study described how select risk factors change over this developmental period and examined developmental changes in the predictive power of these risk factors at various ages. An improved understanding of the developmental course and magnitude of specific eating disorder risk factors before the peak period of onset is vital for the optimal timing of prevention interventions, and an underlying impetus for the present study was to identify when to intervene with early adolescent girls to have the greatest likelihood of reducing risk for eating disorders before their peak period of onset. Risk factors presumably need to be present for the

identification of high-risk populations. Therefore, the present findings support the contention that prevention programs should target young girls at risk for eating disorder onset in early adolescence, potentially at age 14, to maximize intervention effects. The findings lend support to eating disorder prevention programs that target early adolescent girls with body image or weight concerns.[22,29] Methods for reducing body dissatisfaction could include dissonance-based (e.g., standing in front of a mirror and generating positive statements about one's appearance that are shared with the group, role-plays, in which the person works to dissuade the leader from pursuing the unrealistic thin-ideal standard of female beauty) or cognitive-behavioral (e.g., refraining from negative body self-talk, increased exposure to feared body image situations) exercises to counteract body dissatisfaction.[31] In a meta-analytic review of all identified eating disorder programs that were evaluated by controlled trial between 1980 and 2006,[32] there was considerable variation in the range of intervention effects for reducing body dissatisfaction, with cognitive-behavioral treatments aimed at reducing body dissatisfaction having the strongest effects ($r > .50$).[33,34]

Regarding other eating disorder risk factors, perceived pressure to be thin showed the greatest increase in prevalence for young women from ages 13 to 21. Negative affectivity was the only examined risk factor, which significantly decreased from ages 13 to 21 and it is possible that this variable is a relevant risk factor for eating disorder onset during the middle school, compared to the high school, age period. It is also possible that other forms of negative affectivity, perhaps more closely related to anxiety, trauma, and transitional stressors, might have a different developmental course and pattern of association with increased eating disorder risk. On a related note, the construct of negative urgency (i.e., the tendency to act rashly when distressed) in fifth grade children was found to predict an increased expectancy that eating would reduce negative affect and subsequent increases in binge eating behavior 1 year later.[35] Regarding self-reported dieting, rates were generally flat over time, which is consistent with other longitudinal research,[36] although they increased sharply at ages 19–20 among the subset of women who developed an eating disorder during the study; potentially this variable increased as a result, rather than cause, of the eating disorder. It should be noted that controlled research with obese women has failed to find that dieting behaviors significantly increase the risk for the eating disorder symptom of binge eating.[37]

Previous meta-analytic reviews of eating disorder prevention interventions have found significantly weaker effects for programs aimed at adolescents less than 15 years of age compared to prevention interventions with adolescents 15 years of age or older.[32] Though universal psychoeducational prevention interventions with this younger age group have tended to produce nonsignificant effects on eating disorder risk factors,[32] some interactive and media literacy programs have produced significant effects in child or early adolescent samples immediately post-intervention (e.g., body dissatisfaction in girls mean age = 11.8)[38] with some effects remaining to 3-month follow-up (thin-ideal internalization in girls mean age = 10.6;[39] body dissatisfaction in girls mean age = 12.5)[40] or even 12-month follow-up (e.g., dieting and thin-ideal international in girls and boys mean age = 12.9).[41] The finding that more interventions have been found to be effective with older adolescents[32] suggests it might be valuable to adapt eating disorder prevention programs with the strongest evidence bases in middle and late adolescence samples for delivery in early adolescence, as the present study strongly suggests that eating disorder risk factors are elevated by age 13.

Study limitations should be considered when interpreting these findings. First, with the exception of BMI, the predictor variables in this study were based on adolescent report and it is possible that some variation in the findings could be due to differential psychometric properties of the scales. For instance, body dissatisfaction may be easier to assess in a reliable and valid manner, whereas measurement of perceived pressure to be thin, thin-ideal internalization, and dieting is more complicated. However, psychometric properties, both internal consistency and test-retest reliability, for all five questionnaire-based risk factors were respectable and fairly comparable, which suggests that the pattern of results was not biased by measurement differences. Second, we investigated a small subset of putative risk factors for eating pathology and it will be important to investigate additional risk factors that may elucidate other pathways to eating pathology,[42] that could have important implications to the design of eating disorder prevention interventions. Third, results identified common risk factors for eating disorders, rather than disorder-specific risk factors and it is likely that risk factors for specific eating disorder syndromes and specific symptomatic behaviors differ. Although considerably larger studies would be necessary to identify disorder-specific risk factors for each type of eating disorder, this type of

research is needed. Fourth, because the sample contained only women, results cannot be generalized to men. Fifth, as is the case with all longitudinal research, it is possible that some unmeasured variable accounts for the observed prospective effects. Sixth, our focus in this paper was on the course and predictive effects of potential risk factors examined individually, to improve understanding of the developmental patterns and predictive magnitude of each specific potential risk factor; we have previously tested for interactions among risk factors to predict future eating disorder onset across the entire 8-year follow-up period.[17] Given the possibility that some omitted third variable or moderational effects explain the prospective effects observed in longitudinal studies, it will be vital to conduct randomized prevention trials that reduce suspected risk factors with active credible alternative comparison conditions to provide an experimental test of the relation between these risk factors and these eating pathologies.

In sum, it is hoped that prevention programs targeting high-risk populations characterized by the risk factors that predicted eating disorder onset in early adolescence, before peak period of risk for eating disorder onset, will permit more effective prevention efforts. The present findings illustrate that many eating disorder risk factors are present by early adolescence. The results also suggest the need for efficacious eating disorder prevention programs for early adolescent girls, perhaps targeted at age 14, when most risk factors appear to be predictive.

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Abstract

Objective: Prospective studies have identified risk factors that predict future onset of eating disorders, but none has provided a test of a of the temporal sequencing of the emergence of risk factors hypothesized in a multivariate etiologic model of eating disorder development. **Method:** Using data from an 8-year prospective study of 496 adolescent girls, we first conducted receiver operator characteristic plots to identify cut-points for each risk factor that optimally predicted future onset of threshold or subthreshold bulimia nervosa, binge eating disorder, and purging disorder. We then used growth curve models to estimate the age at which each participant crossed the disorder-predictive cut-point for each risk factor, or if they did not, during follow-up, permitting a test of whether the risk factors emerged in the sequence hypothesized in the Dual Pathway etiologic model. **Results:** Overall, 47% of the 51 youth who showed onset of one of these eating disorders first showed emergence of disorder-predictive levels of perceived pressure to be thin and/or thin-ideal internalization, before showing onset of disorder-predictive levels of body dissatisfaction, before showing onset of disorder-predictive levels of dieting and/or negative affect, before showing onset of the eating disorder; another 29% had one of these steps out of order or did not cross one step in this model. Youth who did not show onset of an eating disorder were significantly less likely to cross the disorder-predictive cut-points for each risk factor or to conform to the sequence of risk factor emergence hypothesized in this model. **Conclusions:** Results provide novel support for the temporal sequencing of risk factor emergence hypothesized in this multivariate etiologic model and suggest that prevention programs that reduce perceived pressure to be thin and thin-ideal internalization among early adolescent girls with these factors should reduce eating disorder onset, as well as downstream risk factors that are also aversive (e.g., body dissatisfaction and negative affect).

General Scientific Summary: Finding suggest that typically, eating disorder-predictive levels of perceived pressure to be thin and pursuit of the thin beauty ideal emerge before disorder-predictive levels of body dissatisfaction, which emerge before disorder-predictive levels of dieting and negative affect, which emerge before onset of threshold or subthreshold bulimia nervosa, binge eating disorder, or purging disorder. Results imply that prevention programs should reduce perceived pressure to be thin and pursuit of the thin beauty ideal among early adolescent girls, as this should both reduce eating disorder onset and emergence of aversive downstream risk factors.

Key Words: risk factors, dual pathway model, prospective, bulimia nervosa, binge eating disorder, purging disorder.

Temporal Sequencing of the Emergence of Risk Factors that Predict Onset of Bulimia Nervosa, Binge Eating Disorder, and Purging Disorder

Approximately13% of females will experience an eating disorder at some point in their lives, which are characterized by chronicity, emotional distress, functional impairment, and increased risk for future obesity, depression, suicide, substance abuse, and mortality (Allen, Byrne, Oddy, & Crosby, 2013; Arcelus, Mitchell, Wales, & Nielsen, 2011; Stice, Marti, & Rohde, 2013). It is critical to elucidate factors that predict future onset of eating disorders, as this should inform etiologic theories, which is vital for guiding the content of optimally effective prevention programs and identifying high-risk subpopulations to target with selective prevention programs. Although several prospective studies have identified risk factors that predict future onset of eating disorders, none have provided a rigorous test of a multivariate model that proposes how the risk factors work in concert to predict future eating disorder onset, including the hypotheses regarding the temporal sequencing of risk factor emergence.

The Dual Pathway model is an etiologic theory that hypothesizes how several well-studied psychosocial risk factors may operate together in a meditational fashion to predict future eating disorder onset (Stice, 1994). This theory hypothesizes that pressure for thinness and pursuit of the thin beauty ideal increases risk for subsequent body dissatisfaction, which in turn increases risk for subsequent dietary restriction and negative affect, which in turn increase risk for subsequent onset of eating disorders characterized by binge eating and compensatory weight control behaviors. A previous study provided evidence that pressure to be thin and pursuit of the thin beauty ideal predicted future increases in body dissatisfaction, that body dissatisfaction predicted future increases in dieting and negative affect, and that dieting and negative affect predicted future increases in bulimic symptoms in adolescent girls followed over 2-years (Stice,

2001). However, no prospective study has provided a rigorous test of the *temporal sequencing* of risk factor emergence hypothesized in this multivariate etiologic theory. The goal of the present report is to introduce a new analytic approach for testing hypotheses regarding the temporal sequencing of risk factor emergence in multivariate etiologic models in relation to emergence of clinically significant eating pathology. This analytic approach was specifically developed to test hypotheses regarding the temporal relations among risk factors in multivariate meditational models, and may therefore prove useful for testing hypotheses about the temporal sequencing of risk factor emergence for other public health problems.

One impediment to testing the temporal sequencing of risk factor emergence is that most risk factors are continuous variables, making it challenging to determine at what *age* participants exhibit a *level* of the risk factor that predicts future eating disorder onset. We introduce a three-step approach that might be useful for addressing this important research question. First, receiver operating characteristic (ROC) plots could be used to determine the specific cut-point of a risk factor that optimally predicts future onset of eating disorders, balancing predictive sensitivity and specificity. This approach could be used for each risk factor in a multivariate etiologic model to generate reliable cut-points for each risk factor that optimally predict future eating disorder onset. Second, latent growth curve models could be used to generate individual-level slopes and intercepts that reflect individual differences in the development of each risk factor. These individual slopes and intercepts could then be used to estimate the specific age at which each individual participant initially crossed the cut-points for each risk factor that optimally predict future eating disorder onset, or whether the participant did not cross these cut-points during follow-up. Third, the ages at which participants crossed each cut-point could then be used to test hypotheses regarding the temporal sequencing of risk factor emergence posited in multivariate

meditational etiologic models, such as the Dual Pathway model. This approach would permit a test of the hypothesis that disorder-predictive levels of perceived pressure to be thin and/or internalization of the thin beauty ideal temporally precede emergence of disorder-predictive levels of body dissatisfaction, which in turn temporally precedes emergence of disorder-predictive levels of dieting and/or negative affect, which in turn temporally precede emergence of eating disorders, as proposed *a priori* (Stice, 1994). We hypothesize that adolescent girls who subsequently develop eating disorders would show emergence of disorder-predictive levels of each of these risk factors in this etiologic model, and in the order specified above, whereas adolescent girls who remain eating disorder free will typically not exhibit disorder-predictive levels these risk factors.

Although methodologists often counsel against dichotomizing continuous variables, such as risk factors and eating pathology, the objective of this report is to introduce a novel statistical approach for examining the temporal sequencing of risk factor emergence as it relates to onset of clinically meaningful eating pathology, which seems to necessitate a focus on discrete events that happen at particular developmental points in time. For this reason, we think it might be necessary to dichotomize the risk factors and the pathological outcome, and to translate these discrete events into developmental ages. Further, several studies have established that participants with threshold or subthreshold eating disorders show significant elevations in psychosocial impairment, negative affect, and mental health service utilization (Allen et al., 2013; Stice et al., 2009; 2013). Thus, we elected to predict age of emergence of threshold or subthreshold eating disorders because this is one defensible way of ensuring that the dichotomous outcome captures clinically meaningful eating pathology.

Studies suggest that risk factors that predict future onset of bulimia nervosa, binge eating disorder, and purging disorder are qualitatively distinct from those that predict future onset of anorexia nervosa. Specifically, prospective studies that used diagnostic interviews to assess eating disorder onset have found that social pressure for thinness, pursuit of the thin beauty ideal, body dissatisfaction, dieting, negative affect, alcohol use, low interoceptive awareness, social support deficits, psychosocial impairment, early puberty, overeating, and elevated BMI predicted future onset of threshold or subthreshold bulimia nervosa (Killen et al., 1996; Patton, Johnson-Sabine, Wood, Mann, & Wakeling, 1990; Patton, Selzer, Coffey, Carlin, & Wolfe, 1999; Stice & Bohon, 2013; Stice, Gau, Rohde, & Shaw, 2017; Stice, Marti, & Durant, 2011). Similarly, social pressure for thinness, pursuit of the thin beauty ideal, body dissatisfaction, dieting, negative affect, psychosocial impairment, and overeating predicted future onset of threshold or subthrehold binge eating disorder (Stice et al., 2011; Stice et al., 2017). Likewise, pursuit of the thin beauty ideal, body dissatisfaction, negative affect, dieting, psychosocial impairment, and overeating predicted future onset of threshold or subthreshold purging disorder (Stice et al., 2011a; Stice et al., 2017). In contrast, low BMI, low dieting, and psychosocial impairment predicted onset of threshold or subthreshold anorexia nervosa (Stice & Bohon, 2013; Stice et al., 2017). This pattern of findings implies that the risk factors that predict onset of bulimia nervosa, binge eating disorder, and purging disorder are different from those that predict onset of anorexia nervosa, consistent with the thesis that the dual pathway model predicts emergence of eating disorders characterized by binge eating and compensatory weight control behaviors, rather than anorexia nervosa (Stice, 1994). We therefore offer the more nuanced hypothesis that adolescent girls who subsequently develop threshold or subthreshold bulimia nervosa, binge eating disorder, or purging disorder would show emergence of disorder-predictive levels of each of these risk

factors in the Dual Pathway model, and in the order specified in that model, whereas adolescent girls who subsequently develop threshold or subthreshold anorexia nervosa or who remain eating disorder free will typically not exhibit disorder-predictive levels these risk factors.

An improved understanding of the temporal sequencing of risk factor emergence is important for several reasons. First, it would provide a rigorous test of the temporal patterns articulated in multivariate etiologic models, which is important for advancing etiologic theory for these pernicious disorders. Second, this information should elucidate which risk factor emerges first, which would be a logical target for prevention programs because the interventions might interrupt the etiologic cascade of risk factors that theoretically give rise to eating disorder onset at the earliest possible time. Prevention programs that reduce the earliest emerging risk factor may also reduce downstream risk factors, such as body dissatisfaction and negative affect, which are subjectively distressing, irrespective of whether they eventuate in eating disorder onset. Third, information regarding which disorder predictive risk factor emerges first should also identify high-risk sub-populations to target with selective prevention programs. Targeting those at greatest risk, and as early as possible, may allow for more cost-effective and efficacious prevention efforts for mental health problems.

Methods

Participants and Procedures

Participants were 496 adolescent girls recruited from public and private middle schools in a large US city (7^{th} or 8^{th} grade) who had a mean age of 13 at baseline (*SD* = .71). The sample included 2% Asian/Pacific Islanders, 7% African Americans, 68% Caucasians, 18% Hispanics, 1% Native Americans, and 4% who specified other/mixed racial heritage, which was representative of the schools from which we sampled. There were no ethnic differences in the

likelihood of developing an eating disorder when comparing Caucasian (N = 336) to non-Caucasian (N = 160) participants, $\chi^2(1) = .24$, $p = .628$. Average parental education, a proxy for socioeconomic status, was 29% high school graduate or less, 23% some college, 33% college graduate, and 15% graduate degree, which was representative of the city from which we sampled.

The study was described as an investigation of adolescent mental and physical health. Participants were recruited through an informed consent letter sent to parents of eligible girls that described the study (a second mailing was sent to non-responders). This resulted in a participation rate of 56%, similar to other school-recruited samples that used comparable active consent procedures, structured interviews, and longitudinal follow-up (e.g., 61% for Lewinsohn et al., 2000). Female assessors with at least a bachelor's degree in psychology conducted semi-structured interviews that assessed eating disorder symptoms and recorded participant's weight and height at baseline and seven subsequent years for a total of eight annual assessments (T1 - T8). Assessors attended 24 hours of training wherein they received instruction in structured interview skills, reviewed diagnostic criteria for relevant DSM-IV disorders, observed simulated interviews, and role-played interviews. Assessors were required to demonstrate inter-rater agreement ($k > .80$) with supervisors on tape-recorded interviews prior to collecting data. Assessors also completed annual training workshops to minimize interviewer drift. At each of annual assessment, participants completed questionnaires measuring the risk factors. Participants received a gift certificate or cash for completing each assessment.

Measures

Pressure to be thin. Perceived sociocultural pressure to be thin from family, friends, dating partners, and the media over the past year was assessed with the 10-item Perceived Sociocultural

Pressure Scale (Stice, Marti, & Durant, 2011). Response options ranged from 1 = *none* to 5 = *a lot*. Items were averaged for this scale and those below. This scale has shown internal consistency (α = .88), 2-week test-retest reliability (*r* = .93), and predictive validity for future onset of bulimic symptoms (Stice et al., 2011; α = .85 at T1).

Thin-ideal internalization. The 6-item Ideal-Body Stereotype Scale–Revised assessed pursuit of the thin beauty ideal over the past year (Stice et al., 2011). Response options ranged from 1 = *strongly disagree* to 5 = *strongly agree*. This scale has shown internal consistency (α = .91), 2-week test–retest reliability (*r* = .80), predictive validity for bulimic symptom onset, and sensitivity to intervention effects (Stice et al., 2011; α = .81 at T1).

Body dissatisfaction. The 9-item Body Dissatisfaction Scale (Stice et al., 2001) assessed dissatisfaction with various body parts over the past year. Response options ranged from 1 = *extremely satisfied* to 5 = *extremely dissatisfied*. This scale has shown internal consistency (α = .94), 3-week test–retest reliability (*r* = .90), predictive validity for eating disorder onset, and sensitivity to intervention effects (Stice et al., 2008, 2011; α = .94 at T1).

Dieting. The 10-item Dutch Restrained Eating Scale (van Strien, Frijters, van Staveren, Defares, & Deurenberg, 1986) assesses the frequency of various dieting behaviors over the past year. Response options ranged from 1 = *never* to 5 = *always*. This scale has shown internal consistency (α = .95), 2-week test–retest reliability (*r* = .82), convergent validity with self-reported (but not objectively measured) caloric intake, predictive validity for bulimic symptoms, and sensitivity to intervention effects (Stice et al., 2008; van Strien et al., 1986; α = .91 at T1).

Negative affect. Propensity to become affectively distressed over the past year was assessed with the 12-item Emotionality Scale (Buss & Plomin, 1984). Response options ranged from 1 = *never true of me* to 5 = *always true of me*. This scale showed internal consistency, predictive

validity for onset of bulimic symptoms, and convergent validity with alternative measures of emotionality (Patrick, Curtin, & Tellegen, 2002; Stice et al., 2011; $\alpha = .80$ at T1).

Eating pathology. The semi-structured 30-question Eating Disorder Diagnostic Interview (EDDI; Stice et al., 2013) assessed eating disorder symptoms over the past 3 months at baseline and since previous interview at follow-ups on a month-by-month basis. DSM-IV criteria for eating disorders, as operationalized in Stice et al. (2009), were used. EDDI eating disorder diagnoses have shown sensitivity to intervention effects (Stice et al, 2008). Individuals with EDDI-assessed threshold or subthreshold DSM eating disorders have shown significantly greater psychosocial impairment, emotional distress, and mental health service utilization than individual without these disorders (Stice et al., 2009, 2013), providingh evidence for the validity of DSM eating disorder diagnoses. Diagnoses for threshold and subthreshold eating disorders showed 1-week test-retest reliability (□ = .96) and inter-rater agreement (□ = .86) for a subset of participants in this study (Stice et al., 2009).

Statistical Methods

First, we plotted the ROC curves for the relation of each continuous risk factor, assessed at age 13, 14, 15, and 16, in predicting onset of threshold or subthreshold bulimia nervosa, binge eating disorder, or purging disorder within the next 4 years from each of these ages. The ROC curve illustrates the accuracy with which a risk factor is able to predict a dichotomous outcome in terms of both specificity (i.e., the ability to correctly predict those who will not develop an eating disorder, or true negatives) and sensitivity (i.e., the ability to correctly predict who will develop an eating disorder, or true positives). Each point on the ROC curve represents a sensitivity/specificity combination (or, more accurately, a combination of sensitivity and 1 – specificity) corresponding to a particular value of the predictor (Zweig & Campbell, 1993). ROC

curves can be used to identify the cut-point for the predictor at which both specificity and sensitivity are maximized, which corresponds to the point on the curve closest to the upper left-hand corner of the graph. That is, one uses the cut-point that corresponds to the location of the peak of the ROC graph to determine the cut-point that maximizes both specificity and sensitivity when predicting a dichotomous outcome. We averaged the statistically significant cut-points generated from the plots that separately examined the predictive effects at those 4 ages for each risk factor to generate more reliable cut-points.

Second, because we only assessed the level of each risk factor at one time per year over follow-up, we could not determine the precise age at which each participant crossed the disorder-predictive cut-points for each risk factor. We therefore estimated latent growth models, in which assessments were aligned with participant age, to generate individual slope and intercept values *for each participant* for each risk factor.

To analyze individual growth in risk factor scores, we fit a series of latent growth models for each risk factor using Mplus 7.1 (Muthén & Muthén, 2012), which provides unbiased estimates in the presence of missing data. In each case, we evaluated the relative contribution of both linear and quadratic terms to model fit using the adjusted Bayesian Information Criterion (BIC); the terms were only retained if they contributed to model fit (i.e., the adjusted BIC was smaller). Once the form of each curve was determined, we reported model fit indices, including the chi-square value (χ^2), comparative fit index (CFI), Tucker-Lewis index (TLI), and root-mean squared error of approximation (RMSEA). CFI/TLI values greater than .95, RMSEA values less than 0.5, and a non-significant χ^2 (or a ratio of χ^2/df < 3.0) indicate good fit (Hu & Bentler, 1999). We then derived individual growth curves for each risk factor for each individual. From this, we could estimate the age at which each individual exceeded, or crossed, the cut-points identified in

the first phase of the analysis, if they exceeded the cut-points at any time during follow-up. To ensure that the linear and quadratic growth terms were uncorrelated, we coded the growth parameters such that the intercept would reside in the middle of the curve (i.e., age 17).

Finally, we used these age estimates to test whether participants who subsequently developed threshold or subthreshold bulimia nervosa, binge eating disorder, or purging disorder exhibited the hypothesized sequencing of risk factor emergence or deviated from this sequence. These age estimates also allowed us to test whether participants who did not show onset of one these eating disorders were less likely to show disorder-predictive levels of each risk factor, and whether they typically deviated from the risk factor emergence sequencing hypothesized in the Dual Pathway model.

Results

Preliminary Analyses

The means, standard deviations (SD), and ranges for the risk factors at baseline are presented in Table 1. Participants showed onset of bulimia nervosa (N = 7, 1.4%), subthreshold bulimia nervosa (N = 29, 5.9%), binge eating disorder (N = 3, .6%), subthreshold binge eating disorder (N = 12, 2.5%), purging disorder (N = 19, 3.9%), and subthreshold purging disorder (N = 13, 2.7%).

Cut-Point Analyses

The averaged disorder-predictive cut-points from the ROC models were 1.94 for pressure to be thin, 3.50 for thin-ideal internalization, 3.17 for body dissatisfaction, 2.50 for dieting, and 1.40 for negative affect. The individual cut-points at each age are shown in Table 1. Using individual growth curves for each risk factor, we next calculated the age at which each

participant exceeded each of these cut-points, or whether they never reached the cut-points during the follow-up.

Confirmation of Predictive Validity of Risk Factors

We first evaluated group differences (i.e., those who did not develop an eating disorder over follow-up versus those who did) in terms of their likelihood of exceeding the disorder-predictive cut-points for each risk factor. We used chi-square analysis; the associated contingency tables are presented in Table 2. Participants who did not subsequently develop an eating disorder were less likely to exceed each of the cut-points than those who subsequently developed an eating disorder (though the chi-square analysis for pressure to be thin is only trend-level at $p = .05$). Out of the 429 participants who did not develop an eating disorder, 278 (65%) crossed the cut-point for pressure to be thin; comparatively, 40 of the 51 participants (78%) who developed an eating disorder crossed this cut-point. For the thin-ideal internalization, 228 of 429 (53%) participants who did not develop an eating disorder crossed the cut-point, versus 35 of 51 (69%) of participants who developed an eating disorder. For body dissatisfaction, 178 of 429 (41%) participants who did not develop an eating disorder crossed the cut-point, versus 39 of 51 (77%) of participants who developed an eating disorder. For dieting, 201 of 429 (47%) participants who did not develop an eating disorder crossed the cut-point, versus 42 of 51 (82%) of participants who developed an eating disorder. For negative affect, 223 of 429 (52%) participants who did not develop an eating disorder crossed the cut-point, versus 47 of 51 (92%) of participants who developed an eating disorder.

Although only 5 participants showed onset of threshold or subthreshold anorexia nervosa, for descriptive purposes, we examined how many of these participants crossed the disorder-predictive cut-points. All five (100%) crossed cut-points for pressure to be thin and thin-ideal

internalization, but only one (20%) crossed the cut-point for body dissatisfaction, and three out of the five (60%) crossed the cut-points for dieting and negative affect.

Growth Curve Models for each Risk Factor

Next, we fit growth curves for each risk factor. For the pressure to be thin model, both the linear (6108.69 vs. 6289.10) and quadratic terms (6045.83 vs. 6108.69) contributed to model fit and were retained; the final model demonstrated good fit [CFI = 1.00, TLI = 1.00, RMSEA = .02, $\chi^2(27) = 31.91$, $p = .196$]. For thin-ideal internalization, both the linear (6153.54 vs. 6285.89) and quadratic terms (6107.45 vs. 6153.54) contributed to model fit and were retained; the final model demonstrated good fit [CFI = .98, TLI = .98, RMSEA = .05, $\chi^2(27) = 64.25$, $p < .001$]. For body dissatisfaction, both the linear (6974.08 vs. 7040.61) and quadratic terms (6950.69 vs. 6974.08) contributed to model fit and were retained; the final model demonstrated good fit [CFI = .97, TLI = .97, RMSEA = .05, $\chi^2(27) = 66.58$, $p < .001$]. For dieting, both the linear (7616.20 vs. 7800.76) and quadratic terms (7522.03 vs. 7616.20) contributed to model fit and were retained; the final model demonstrated good fit [CFI = .98, TLI = .98, RMSEA = .05, $\chi^2(27) = 66.37$, $p < .001$]. For negative affect, both the linear (2085.49 vs. 2262.28) and quadratic terms (2031.27 vs. 2085.49) contributed to model fit and were retained; the final model demonstrated good fit [CFI = .98, TLI = .98, RMSEA = .05, $\chi^2(27) = 49.53$, $p < .001$]. Data for the mean growth curves are presented in Table 3.

For descriptive purposes, we examined the percentage of participants who crossed the various disorder-predictive cut-points, and the mean ages at which this occurred, among those who crossed each cut-point. The percentages and mean ages were as follows: pressure to be thin (N = 333 out of 496 or 67%, M age = 14.77, SD = 2.22); thin-ideal internalization (N = 273 out of 496 or 55%, M age = 14.82, SD = 2.17); body dissatisfaction (N = 228 out of 496 or 46%, M

age = 14.20, *SD* = 2.19); dieting (*N* = 254 out of 496 or 51%, *M* age = 14.55, *SD* = 2.32); and, negative affect (*N* = 283 out of 496 or 57%, *M* age = 14.49, *SD* = 2.07).

Test of Temporal Sequencing of Risk Factors in the Dual Pathway Model

We then examined the percent of participants who eventually showed onset on an eating disorder that showed the predicted temporal sequencing of risk factor emergence posited by the Dual Pathway Model. Overall, 24 of the 51 participants who developed an eating disorder (47%) followed the hypothesized pathway (see Table 4). Specifically, these 24 participants showed emergence of disorder-predictive levels of pressure to be thin and/or thin-ideal internalization before they showed emergence of disorder-predictive levels of body dissatisfaction, which occurred before they showed onset of disorder-predictive levels of dieting and/or negative affect, which occurred before they showed onset of the eating disorder. For these participants, the average lag time for the first step (pressure to be thin and/or thin-ideal internalization to body dissatisfaction) was 1.0 months (*SD* = .41), the average lag time for the second step (body dissatisfaction to dieting and/or negative affect) was 8.0 months (*SD* = 1.61), and the average lag time for the third step (dieting and/or negative affect to emergence of an eating disorder) was 26.8 months (*SD* = 1.93).

Another 8 participants (16%) crossed each threshold in the hypothesized pathway, but had one step out of order. Of the remaining 19 participants, 7 (14%) crossed thresholds at two steps in the pathway; they tended to map onto the latter portion, although two participants had a step out of order (see Table 4). Eleven participants crossed one step in the pathway, and of these, again the majority followed the latter portion, with two participants having one step out of order (see Table 4). Finally, one participant did not cross enough thresholds for us to map any step.

For the 429 participants who did not develop an eating disorder over the 8-year follow-up, none by definition fulfill the final step in the hypothesized pathway (i.e., dieting and/or negative affect → eating disorder). However, there were 112 (26%) who surpassed enough of the thresholds for us to map the first two steps in the hypothesized pathway. Among these participants, 93 (22%) demonstrated the first two steps in the pathway (i.e., pressure to be thin and/or thin-ideal internalization → body dissatisfaction, and body dissatisfaction → dieting and/or negative affect); for 11 (3%) participants, pressure to be thin and/or thin-ideal internalization emerged after body dissatisfaction, and for 8 (2%) participants, body dissatisfaction emerged after dieting and/or negative affect. Of the 54 participants (13%) who surpassed enough thresholds for us to map one step in the hypothesized pathway, 30 (7%) demonstrated the first step in the pathway (pressure to be thin and/or thin-ideal internalization → body dissatisfaction), and 22 (5%) demonstrated the second step in the pathway (body dissatisfaction → dieting and/or negative affect); for one participant, thin and/or thin-ideal internalization emerged after body dissatisfaction. The remaining 263 participants (61%) in the sample did not surpass enough thresholds for us to map any step in the hypothesized pathway.

It is possible that some participants who showed eating disorder onset did not conform to the hypothesized temporal sequencing of risk factor emergence because they were from ethnic minority groups that might have different appearance ideal than ethnic majority participants. However, among those participants who developed an eating disorder ($N = 51$), there were no ethnic differences in the likelihood of following the hypothesized temporal sequencing of risk factor emergence when comparing Caucasian ($n = 33$) to non-Caucasian ($n = 18$) participants: $\chi^2(1) = .75, p = .388$.

For descriptive purposes, we evaluated the pathways for the 5 participants who subsequently showed onset of threshold or subthreshold anorexia nervosa. Of these, two had a co-morbid non-anorexia nervosa diagnosis and were already considered above. Of the remaining three, none of them demonstrated the hypothesized sequence of risk factor emergence from the Dual Pathway Model. In general, pressure to be thin and/or thin-ideal internalization emerged later instead of earlier.

Exploratory Analyses

The Dual Pathway model theorizes how a set of well-characterized risk factors work together to predict future eating disorder onset, focusing on culture pressures to conform to the thin beauty ideal and risk factors that theoretically occur in response to these pressures. Yet, the literature review revealed that several other risk factors have been found to predict future onset of any eating disorder, including low parental support, low peer support, and psychosocial impairment. As we measured these risk factors in the present study, it afforded an opportunity to conduct exploratory analyses that about when disorder-predictive levels of these more recently identified risk factors emerge in comparison to the risk factors in the Dual Pathway Model. Specifically, we tested the hypothesis that low social support from parents, low social support from peers, and psychosocial impairment increase risk for future onset of disorder-predictive levels of thin-ideal internalization, as adolescent girls may pursue the culturally sanctioned appearance ideal to gain social acceptance. Perceived social support was measured with Network of Relationships Inventory (Furman, 1996) items assessing companionship, guidance, intimacy, affection, admiration, and reliable alliance from parents and peers (6 items each). These scales have shown internal consistency (M $\alpha = .88$), 4-week test-retest reliability (M $r = .69$), and predictive validity (Furman, 1996; Stice, Ragan, & Randall, 2004). Psychosocial impairment in

the family, peer group, romantic, and school domains was measured with 17 items from the Social Adjustment Scale-Self Report for Youth (Weismann & Bothwell, 1976). This scale has shown internal consistency (α = .77), 1-week test–retest reliability (r = .83) and sensitivity to intervention effects (Stice et al., 2008b).

The averaged cut-points from the ROC plots were 4.17 for parental support, 4.67 for peer support, and 2.55 for psychosocial impairment. With regard to the percentage of participants who crossed the various disorder-predictive thresholds, and the mean ages at which this occurred, among those who crossed each threshold, we found the following: parental support (N = 252 out of 496 or 51% crossed the disorder-predictive cut-point and did so at a mean age = 13.00, SD = .50); peer support (N = 415 out of 496 or 84% crossed the disorder-predictive cut-point; M age = 13.00, SD = .20); and psychosocial impairment (N = 423 out of 496 or 85% crossed the disorder-predictive cut-point, M age = 13.02, SD = .31). We next tested whether participants who later showed onset of an eating disorder were more likely to cross these disorder-predictive cut-points versus participants who did not show eating disorder onset. Out of the 429 adolescent girls who did not develop an eating disorder, 213 (50%) crossed the cut-point for low parental support; comparatively, 31 of the 51 participants (61%) who developed an eating disorder crossed this cut-point; this difference was not significant, $\chi^2(1) = 2.26$, p = .133. For low peer support, 360 of 429 (84%) participants who did not develop an eating disorder crossed the cut-point, compared to 43 of 51 (84%) of participants who developed an eating disorder; this difference weas not significant, $\chi^2(1) = .01$, p = .942. For psychosocial impairment, 363 of 429 (85%) participants who did not develop an eating disorder crossed the cut-point, compared to 49 of 51 (96%) of participants who developed an eating disorder; this difference is not significant, $\chi^2(1) = 2.57$, p = .109.

We next estimated the growth curve models for these three risk factors. For parental support, both the linear (8097.44 vs. 8219.22) and quadratic terms (8016.93 vs. 8097.44) contributed to model fit and were retained; the final model showed good fit [CFI = .97, TLI = .97, RMSEA = .05, $\chi^2(27) = 65.38$, $p < .001$]. For peer support, both the linear (7741.71 vs. 7812.26) and quadratic terms (7739.24 vs. 7741.71) contributed to model fit and were retained; the final model showed good fit [CFI = .95, TLI = .95, RMSEA = .05, $\chi^2(27) = 64.43$, $p < .001$]. For psychosocial impairment, both the linear (3332.73 vs. 4085.42) and quadratic terms (3302.52 vs. 3332.73) contributed to model fit and were retained; the final model showed moderate fit [CFI = .90, TLI = .89, RMSEA = .10, $\chi^2(27) = 101.88$, $p < .001$].

Among the 51 participants who developed an eating disorder, 20 (39%) showed emergence of disorder-predictive levels of low parental support before showing emergence of disorder predictive levels of thin-ideal internalization, 29 (57%) showed emergence of disorder-predictive levels of low peer support before showing emergence of disorder predictive levels of thin-ideal internalization, and 33 (65%) showed emergence of disorder-predictive levels of psychosocial impairment before showing emergence of disorder-predictive levels of thin-ideal internalization. Out of the 429 participants who did not develop an eating disorder, 117 (27%) showed emergence of disorder-predictive levels of low parental support before showing emergence of disorder predictive levels of thin-ideal internalization, 195 (45%) showed emergence of disorder-predictive levels of low peer support before showing emergence of disorder predictive levels of thin-ideal internalization, and 197 (46%) showed emergence of disorder-predictive levels of psychosocial impairment before showing emergence of disorder-predictive levels of thin-ideal internalization.

Discussion

To our knowledge, this is the first study to investigate the temporal sequencing of the emergence of risk factors for binge eating and compensatory weight control behavior eating disorders hypothesized on an *a priori* basis (Stice, 1994). Specifically, the Dual Pathway theory postulates that pressure to be thin and internalization of the thin beauty ideal results in subsequent emergence of body dissatisfaction, which results in subsequent emergence of dieting and negative affect, which increases risk for subsequent emergence of eating disorders characterized by binge eating and/or compensatory weight control behaviors. We used data from a community sample of 496 adolescent girls who completed annual diagnostic interviews over an 8-year follow-up, which afforded a unique opportunity to examine the temporal sequencing of risk factor emergence during adolescence.

The first step in the novel analytic technique for testing hypotheses about the temporal sequencing of risk factor emergence is to determine the levels of each risk factor that optimally predict future eating disorder onset. We plotted ROC curves that generated cut-points that optimally predicted future eating disorder onset, balancing sensitivity and specificity, using data collected at age 13, 14, 15, and 16 to predict eating disorder onset over the subsequent 4 years in each of the 4 ROC plots. We then averaged the cut-points identified in each of the ROC plots for each of the 5 risk factors and used results from the latent growth curve models to determine the age at which *each participant* crossed each disorder-predictive cut-point. The average cut-point for pressure to be thin was 1.9, which corresponded to the response option between *none* and *some*; 67% of the sample crossed this threshold at an average age of 14.8. The average cut-point for thin-ideal internalization was 3.5, which corresponded to the response option of *agree*; 55% of the sample crossed this threshold at an average age of 14.8. The average cut-point for body dissatisfaction was 3.2, which corresponded to the response option between *neutral* and

moderately dissatisfied; 46% of the sample crossed this threshold at an average age of 14.2. The average cut-point for dieting was 2.5, which corresponded to a response option of *sometime;* 51% of the sample crossed this threshold at an average age of 14.6. The average cut-point for negative affect was 1.4, which corresponded to a response option of *agree*; 57% of the sample crossed this threshold at an average age of 14.5. The fact that on average participants crossed these disorder-predictive cut-points between the ages of 14.2 and 14.8, suggests that it might be optimal to implement eating disorder prevention programs around the age of 13 or 14 to reduce these particular intervention targets.

We next tested whether participants who showed onset of an eating disorder during follow-up were significantly more likely to cross the various disorder-predictive cut-points for each examined risk factor than participants who did not develop an eating disorder. In total, 51 participants who were free of an eating disorder at baseline, when the modal age was 13, showed onset of threshold or subthreshold bulimia nervosa, binge eating disorder, or purging disorder over 8-year follow-up. Analyses confirmed that participants who showed eating disorder onset were significantly more likely to cross each of the disorder-predictive thresholds than participants who did not develop an eating disorder. These results thus provide evidence of the predictive validity of the identified cut-points for these risk factors.

The final step in this novel analytic approach was to determine the percentage of participants who subsequently showed eating disorder onset who exhibited the temporal sequencing of risk factor emergence hypothesized in the Dual Pathway model. Overall, 47% of participants showed emergence of disorder-predictive levels of pressure to be thin and/or thin-ideal internalization before they showed emergence of disorder-predictive levels of body dissatisfaction, which occurred before they showed onset of disorder-predictive levels of dieting and/or negative affect,

which occurred before they showed onset of an eating disorder. Although only 47% of participants who showed onset of an eating disorder exhibited the temporal sequencing of risk factor emergence hypothesized in this model, the null hypothesis would be that only 4% of participants would have been expected to show this particular temporal sequencing (4 x 3 x 2 = 24; 1/24 = .04%). Thus, the fact that 47% of the participants who showed onset of an eating disorder was greater than the 4% expected based on chance provides reasonable support for the hypothesized temporal sequencing of risk factor emergence. Another 16% of participants crossed each cut-point in the hypothesized pathway, but had one step out of order. Further, 14% of participants crossed cut-points at two steps in the pathway, although 2 participants had a step out of order. Thus, 77% of participants conformed to the predicted temporal sequencing of risk factor emergence, or had 1 step out of order or missed only 1 step in the hypothesized etiologic sequence, which provides reasonable support for the temporal sequencing of risk factor emergence hypothesized in the Dual Pathway Model.

Nonetheless, the fact that among those who showed eating disorder onset, 16% had one step out of order implies that the investigated risk factors may show bi-directional relations (e.g., that elevated body dissatisfaction might lead some adolescent girls to subsequently perceive greater pressure for thinness, or that elevated negative affect might contribute to subsequent increases in body dissatisfaction). Further, the fact that another 14% did not cross all cut-points seems to imply that some risk factors may directly increase risk for onset of eating disorders, rather than operating through the hypothesized mediators (e.g., that elevated body dissatisfaction may contribute directly to emergence of compensatory weight control behaviors without first prompting dieting and negative affect). It would be very useful for future research to investigate the most common deviations from the etiologic process hypothesized in this etiologic model

using larger data sets, as it is possible that there are qualitatively distinct pathways to onset of these eating disorders that are reliable. It is important to acknowledge that a deviation from the hypothesized temporal sequencing of risk factor does not necessarily mean that the risk factor was not endorsed for those participants, as the risk factor scores might have been just below the disorder-predictive cut-points that we generated.

The data on the average lag between steps for those who conformed to the Dual Pathway Model was also intriguing. Emergence of disorder-predictive levels of body dissatisfaction occurred very rapidly after emergence of disorder-predictive levels of pressure for thinness and thin-ideal internalization, averaging only 1 month. This implies that pressure for thinness and pursuit of the thin beauty ideal may very rapidly result in body dissatisfaction. In contrast, emergence of disorder predictive levels of dieting or negative affect did not occur for an average of 8 months after emergence of disorder-predictive levels of body dissatisfaction, suggesting adolescent girls typically experience prolonged body dissatisfaction before turning to dieting to conform to the thin beauty ideal or experiencing the emergence of negative affect. Strikingly, eating disorders emerged a full 27 months on average after disorder-predictive levels of dieting or negative affect emerged, implying that the risk from these latter two risk factors accumulate over a very extended period before eating disorder emergence.

We also conducted exploratory analyses that investigated the hypothesis that disorder-predictive levels of low parental support, low peer support, and psychosocial impairment emerge before disorder-predictive levels of thin-ideal internalization, as the former three risk factors have been found to predict future onset of any eating disorder after the Dual Pathway Model was proposed. According to the ROC curves, the average cut-point for low parental support was 4.17, which corresponded to the response option of *agree*; 51% of the sample crossed this cut-point at

an average age of 13.0. The average cut-point for low peer support was 4.67, which corresponded to the response option of *strongly agree*; 84% of the sample crossed this cut-point at an average age of 13.0. The average cut-point for psychosocial impairment was 2.55, which corresponded to the response option of *sometimes*; 85% of the sample crossed this cut-point at an average age of 13.0. However, participants who showed eating disorder onset during follow-up were not significantly more likely to cross the disorder-predictive cut-points for these three risk factors that those who did not show eating disorder onset, suggesting these risk factors show less robust relations to future eating disorder onset than the other examined risk factors. Nonetheless, results provided support for our hypothesis that disorder-predictive levels of low parental support, low peer support, and psychosocial impairment temporally precede emergence of disorder-predictive levels of thin-ideal internalization, based on the theory that adolescent girls might pursue the culturally sanctioned thin beauty ideal to gain social acceptance. Of the 51 participants who subsequently developed an eating disorder, 39% showed emergence of disorder-predictive levels of low parental support before showing emergence of disorder predictive levels of thin-ideal internalization, 57% showed onset of disorder-predictive levels of low peer support before showing onset of disorder-predictive levels of thin-ideal internalization, and 65% showed emergence of disorder-predictive levels of psychosocial impairment before showing emergence of disorder-predictive levels of thin-ideal internalization. Thus, these exploratory analyses suggest that these three variables that tap into the broader construct of social support and functioning often emerge before pursuit of the thin beauty ideal emerges.

More generally, the present results suggest that this new analytic approach for testing hypotheses about the temporal sequencing of risk factor emergence represents a potentially useful method for evaluating multivariate etiologic models for psychological disorders or other

public health problems. Indeed, this analytic technique might be viewed as an extension of procedures for testing meditational hypotheses (e.g., Baron & Kenny, 1986; Kraemer, Stice, Kazdin, & Kupfer, 2001; Stice, Presnell, Gau, & Shaw, 2007). Although it is necessary to measure risk factors and the public health problem numerous times over a long developmental span, this analytic approach appears to represent a rigorous method of testing complex multivariate meditational etiologic models.

It is important to consider study limitations. First, although participants completed annual assessments from age 13 to 20, it would have been ideal if participants had provided data at younger and older ages to produce a more complete characterization of the emergence of the risk factors and eating disorders. Second, the examined risk factors involved variables implicated in sociocultural etiologic models of eating disorders. It would be useful if future studies included any biological risk factors that are eventually found to predict future eating disorder onset. Third, although the novel analytic technique is useful in documenting temporal precedence, it does not establish causality, which requires experimental manipulation of the risk factors in a design that controls for potential alternative explanations for reductions in the incidence of eating disorders in the sample (e.g., expectancies or demand characteristics). Fourth, we did not adjust alpha to correct for chance findings that might have emerged because of multiple testing. However, the fact that we only conducted eight inferential tests (whether the disorder-predictive levels of each risk factor were more likely to occur in those who did versus did not develop an eating disorder) suggests that not even one effect would have been expected based on chance.

Results suggest that prevention programs should seek to reduce pursuit of the thin beauty ideal and social pressure for thinness among adolescent girls around the ages of 13 to 14, as this should not only reduce risk for future eating disorders, but also reduce the risk for emergence of

body dissatisfaction, unhealthy dieting behaviors, and negative affect. Although eating disorder prevention programs that reduce pursuit of the thin beauty ideal have been developed, it would be useful if prevention programs also targeted pressure for thinness (e.g., by also intervening with parents, siblings, and peers). In addition, the exploratory analyses suggested that it might also be useful to evaluate prevention programs that seek to improve social support and psychosocial functioning, as these risk factors have not been directly targeted in eating disorder prevention programs.

It will be important for future studies to investigate how the other risk factors that have been found to predict future eating disorder onset work in concert with the risk factors examined herein, as this should continue to advance our understanding of the etiologic processes that give rise to these pernicious psychological disorders. Another useful direction for future research would be to develop an analytic approach that can be used to test hypotheses about the temporal sequencing of risk factor emergence using continuous variables to represent risk factors and psychopathology. For instance, with enough assessments it should be possible to fit higher order polynomials and then calculate derivatives that identify the age at which each participant shows an initial increase in each risk factor and eating disorder symptom dimension.

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Table 1. *Descriptive data and cut-points for risk factors*

	Baseline data	*Cut-points*				
Risk Factor	*M (SD), range*	*Age 13*	*Age 14*	*Age 15*	*Age 16*	*Overall*
Pressure to be thin	1.82 (.81), 1.00-5.00	2.00	1.88			1.94
Thin-ideal internalization	3.25 (.72), 1.00-5.00	3.50				3.50
Body dissatisfaction	2.80 (1.02), 1.00-5.00	3.33	3.00	3.22	3.11	3.17
Dieting	2.22 (.92), 1.00-5.00	2.56			2.44	2.50
Negative affect	1.34 (.37), 1.00-3.15	1.38	1.38	1.46	1.38	1.40

Table 2. *Contingency tables evaluating rates at which ED vs. non-ED crossed each threshold*

	Pressure to be thin		*Thin-ideal internalization*		*Body dissatisfaction*		*Dieting*		*Negative Affect*	
	No	*Yes*	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*
No ED										
Observed count	151	278	201	228	251	178	228	201	206	223
Expected count	144.8	284.2	193.9	235.1	235.1	193.9	211.8	217.2	187.7	241.3
Non-anorexia ED										
Observed count	11	40	16	35	12	39	9	42	4	47
Expected count	17.2	33.8	23.1	27.9	27.9	23.1	25.2	25.8	22.3	28.7
Chi-square test	$\chi^2(1) = 3.79$, $p = .052$		$\chi^2(1) = 4.41$, $p = .036$		$\chi^2(1) = 22.51$, $p < .001$		$\chi^2(1) = 22.98$, $p < .001$		$\chi^2(1) = 29.90$, $p < .001$	

Table 3. *Descriptive data for mean growth curve for each risk factor*

	Pressure to be thin		*Thin-ideal internalization*		*Body dissatisfaction*		*Dieting*		*Negative affect*	
	M	*Var*	*M*	*Var*	*M*	*Var*	*M*	*Var*	*M*	*Var*
Intercept	1.961	.428	3.335	.357	2.871	.519	2.084	.476	1.442	.106
Linear slope	.052	.013	.025	.006	.009	.015	.010	.017	.016	.001
Quadratic slope	.002	.002	-.001	.001	-.003	.002	.007	.002	-.003	< .001

Note. *M* = mean. *Var* = variance. Growth curve parameters are coded such that the intercept is at age 17.

Table 4. *Patterns for those who developed an eating disorder (N = 51)*

	PTBT/TI → BD	*BD → Diet/Neg*	*Diet/Neg → ED*
Exceeded cut point at three steps			
All three steps in the pathway (*n* = 24)	Yes	Yes	Yes
Middle/Late pathway (*n* = 4)	No	Yes	Yes
Early/Late pathway (*n* = 2)	Yes	No	Yes
Early/Middle pathway (*n* = 1)	Yes	Yes	No
Middle pathway only (*n* = 1)	No	Yes	No
Exceeded cut point at two steps			
Middle/Late pathway (*n* = 5)		Yes	Yes
Late pathway only (*n* = 2)		No	Yes
Exceeded cut point at one step			
Late pathway only (*n* = 9)			Yes
No pathway (*n* = 2)			No
No cut points crossed (*n* = 1)			

Note. PTBT: Pressure to be thin. TI: Thin ideal. BD: Body Dissatisfaction. Diet: Dieting. Neg: Negative affect. ED: Eating disorder.

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EMPIRICAL RESEARCH

Adolescents' Social Network Site Use, Peer Appearance-Related Feedback, and Body Dissatisfaction: Testing a Mediation Model

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Abstract Previous correlational research indicates that adolescent girls who use social network sites more frequently are more dissatisfied with their bodies. However, we know little about the causal direction of this relationship, the mechanisms underlying this relationship, and whether this relationship also occurs among boys to the same extent. The present two-wave panel study (18 month time lag) among 604 Dutch adolescents (aged 11–18; 50.7 % female; 97.7 % native Dutch) aimed to fill these gaps in knowledge. Structural equation modeling showed that social network site use predicted increased body dissatisfaction and increased peer influence on body image in the form of receiving peer appearance-related feedback. Peer appearance-related feedback did not predict body dissatisfaction and thus did not mediate the effect of social network site use on body dissatisfaction. Gender did not moderate the findings. Hence, social network sites can play an adverse role in the body image of both adolescent boys and girls.

Keywords Social media · Body image · Gender · Peer influence · Appearance ideals · Adolescence

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Introduction

Body image plays an important role in adolescent development and wellbeing (Markey 2010). The body changes significantly during adolescence and adolescents need to cope with these changes (Markey 2010). Although many adolescents display some dissatisfaction with their bodies during this period, a high level of body dissatisfaction is a significant threat to adolescents' wellbeing (Markey 2010). Adolescents who are more dissatisfied with their physical appearance are at an increased risk for suffering from, for example, depression, eating disorders, and low self-esteem (as reviewed by Markey 2010). As a result, the public and academics are keen to identify factors that contribute to body dissatisfaction (Markey 2010). The current study explores such a potential factor by investigating the effect of social network site use on body dissatisfaction.

The effect of social network sites on the lives and the development of adolescents is important to investigate given the role social network sites currently play in adolescents' lives (O'Keeffe and Clarke-Pearson 2011). Social network sites are ubiquitous among adolescents: 70 % of European adolescents aged 14–17 use social network sites and 40 % of these users spend over 2 hours per day on these websites (Tsitsika et al. 2014). Social network sites consist of personal profiles of users (Pempek et al. 2009). Users present oneself to others on these profiles through text and pictures, they view and comment on the self-presentations of other users, and they read others' comments on the own self-presentations (Espinoza and Juvonen 2011; Pempek et al. 2009). Personal photographs and physical appearance play an important role in these social network site activities (Ringrose 2011; Siibak 2009). Therefore, researchers have started to ask whether social

network sites impact body image (e.g., Tiggemann and Miller 2010; Tiggemann and Slater 2013).

We currently know little about the effect of social network sites on body image. In two correlational studies, adolescent girls (aged 13–18 and 13–15) who used social network sites more frequently were more dissatisfied with their bodies (Tiggemann and Miller 2010; Tiggemann and Slater 2013). However, at least three important gaps remain in our knowledge about the relationship between the use of social network sites and adolescents' body image. First, existing research on the effects of social network site use on body image is generally limited to cross-sectional data (Tiggemann and Miller 2010; Tiggemann and Slater 2013). These studies show that individuals who are more dissatisfied with their appearance *at the same time* use social network sites more frequently. However, we do not know whether social network site use is related to *changes* in adolescents' body dissatisfaction over time (Tiggemann and Miller 2010; Tiggemann and Slater 2013). The first aim of the current study is therefore to test if frequency of social network site use predicts changes in body dissatisfaction among adolescents over time.

Second, we currently do not know which mechanisms explain the initial association found between social network site use and body image (Tiggemann and Miller 2010; Tiggemann and Slater 2013). In previous research, media use was indirectly associated with body dissatisfaction through peer influence (Clark and Tiggemann 2006). Girls aged nine to 12 who were exposed to appearance-focused TV and magazines more frequently at the same time reported having conversations about appearance with peers more frequently, which, in turn, was related to greater body dissatisfaction (Clark and Tiggemann 2006). Other studies have highlighted the impact that peers have on the body image of adolescents and adults of different ages (Eisenberg et al. 2003; Jones et al. 2004; Thompson et al. 1999a). We currently do not know if the use of social network sites also influences peers' exchanges about physical appearance and if social network sites also impact adolescents' body dissatisfaction indirectly through peer influence. The second aim of this study is therefore to test whether the use of social network sites affects body dissatisfaction indirectly through peer influence in the form of increased reception of peer appearance-related feedback.

Third, research on the effect of social network site use on body image has predominantly focused on girls (Tiggemann and Miller 2010; Tiggemann and Slater 2013). We understand this focus on girls because body image problems are more prevalent among adolescent girls than boys (O'Dea and Caputi 2001). However, adolescent boys also experience body dissatisfaction (McCabe and Ricciardelli 2001). Furthermore, some factors that affect girls' body image also impact boys' body image (as reviewed by Ricciardelli and McCabe 2004). The third aim of our study is therefore to investigate the relationships between social network site use, peer appearance-related feedback, and body dissatisfaction among both boys and girls and to establish if and how these factors and processes differ between boys and girls.

The tripartite influence model of body image, which is also referred to as the sociocultural model of body image, is a useful conceptual framework for investigating body image (Thompson et al. 1999b). This model describes that a variety of sociocultural channels, notably individuals' parents, peers, and the media, convey beauty ideals to individuals (Thompson et al. 1999b). According to this model, individuals internalize these beauty ideals, and, to the extent that their own appearance does not match these ideals, become dissatisfied with their appearance (Thompson et al. 1999b). As most people do not think that they look like the ideal (Jacobi and Cash 1994), the vast majority of individuals will become more dissatisfied with their bodies when they evaluate the degree to which they match the appearance ideals (Thompson et al. 1999b). In this way, sociocultural channels contribute to body dissatisfaction.

Research among adolescents aged 10–15 has supported the notion that the media, parents, and peers influence adolescents' body dissatisfaction (Keery et al. 2004; Shroff and Thompson 2006; Stanford and McCabe 2005) in line with predictions of the tripartite influence model (Thompson et al. 1999b). Studies that dealt with the effects of media, such as TV and magazines, have typically focused on the effects of exposure to highly idealized images of physically attractive people and appearance-focused content on body dissatisfaction [for meta-analyses see Bartlett et al. 2008 (males); Groesz et al. 2002 (females)]. However, few studies in the field of body image have paid attention to the changing media landscape and the rise of online media, such as social network sites (for notable exceptions see Meier and Gray 2013; Tiggemann and Miller 2010; Tiggemann and Slater 2013). The current study investigates if and how social network sites impact body image among adolescent boys and girls using the tripartite model of influence on body image as a framework.

The Current Study

Initial research into adolescents' activities and experiences on social network sites suggests that social network site use exerts a sociocultural influence on adolescents' body image (Ringrose 2011; Siibak 2009). Physical appearance plays a central role in adolescents' activities and experiences on different social network sites (Ringrose 2011; Siibak

2009). Social network site activities at least partly revolve around personal photographs (Espinoza and Juvonen 2011). When reporting on their most common social network site activities, 60 % of adolescents aged 12–13 named adding pictures to their profiles and 46 % named looking at other's pictures (Espinoza and Juvonen 2011). Furthermore, adolescents choose pictures to upload to their social network site profile at least partly based on their physical appearance in the photograph (Siibak 2009). Among adolescents aged 11–18, 56 % of girls and 31 % of boys report good looks as the most relevant factor for choosing a picture to upload to their social network site profile (Siibak 2009). Furthermore, adolescent girls aged 14–16 report in interviews that they are very concerned with their physical appearance on social network sites (Ringrose 2011). These girls edited their photos to create a physically attractive representation of themselves on their profile and often received comments on their looks (Ringrose 2011).

According to the tripartite influence model (Thompson et al. 1999b), sociocultural influences to look attractive contribute to body dissatisfaction, as individuals generally do not meet the sociocultural beauty ideals (Jacobi and Cash 1994). If, as previous research suggests, social network site use exerts a sociocultural influence on body image (Ringrose 2011; Siibak 2009), the tripartite model would thus predict that social network site use will lead to body dissatisfaction. In line with the notion that social network site use exerts a negative influence on body image, some studies have initially shown that social network site use is negatively related to body image among adolescent girls aged 13–18 (Tiggemann and Miller 2010; Tiggemann and Slater 2013). Based on the tripartite influence model (Thompson et al. 1999b) and the evidence that social network sites exert a sociocultural influence on body image (Ringrose 2011; Siibak 2009), the most likely explanation of this correlation is that social network site use leads to increased body dissatisfaction. We, therefore, hypothesized that more frequent social network site use predicts increased body dissatisfaction among adolescents (H1).

The use of appearance-focused media can also impact the degree of appearance-focus in adolescents' peer-exchanges. The use of appearance-focused media may contribute to an "appearance culture" among peers (Jones et al. 2004), which includes talking about each other's physical appearance and how to improve it. In line with this notion, research among girls aged nine to 12 shows that girls who more frequently use appearance-focused media (television and magazines) also have conversations about their appearance with their peers more often (Clark and Tiggemann 2006). Scholars have proposed that the appearance ideals that adolescents see in the media become personalized when they talk with peers (Clark and Tiggemann 2006; Jones et al. 2004). The use of appearance-focused media may, therefore, lead adolescents to more frequently receive appearance-related feedback from peers.

Because social network sites are also focused on appearance to a great extent (Ringrose 2011; Siibak 2009; Wang et al. 2010), the use of social network sites may also lead adolescents to more often exchange feedback on each other's physical appearance. For example, adolescents may talk about the pictures they and others have posted on a social network site in later conversations with their friends. Peers may evaluate the physical appearance of themselves and others and exchange tips to improve their looks. Adolescents can exchange this peer appearance-related feedback both within and outside of the social network site platform. In this way, adolescents' use of social network sites may lead them to receive peer appearance-related feedback more frequently. To our knowledge, previous research has not investigated whether social network site use indeed impacts appearance-related exchanges among peers in such a way. However, based on research on other appearance-related media (Clark and Tiggemann 2006), we hypothesized that more frequent social network site use predicts increased peer appearance-related feedback among adolescents (H2a).

According to the tripartite model, the reception of peer appearance-related feedback will negatively impact adolescents' body image (Thompson et al. 1999b). Peer appearance-related feedback pressures adolescents to conform to an appearance ideal that they do not meet (Thompson et al. 1999b). Adolescents become aware of discrepancies between their own bodies and the appearance ideal and, as a result, become dissatisfied with their appearance (Thompson et al. 1999b). In line with this prediction, adolescents (aged 12–17) who received peer appearance-related feedback more frequently were less satisfied with their bodies (Eisenberg et al. 2003; Jones et al. 2004). Therefore, we hypothesized that more frequent reception of peer appearance-related feedback predicts greater body dissatisfaction among adolescents (H2b).

Media may impact adolescents' body image indirectly through peer influence (Clark and Tiggemann 2006; Jones et al. 2004). Among girls aged nine to 12, exposure to appearance-focused magazines and TV was not related to body dissatisfaction directly, but only indirectly through appearance conversations with peers (Clark and Tiggemann 2006). The use of appearance-focused media (television and magazines) was related to more frequent conversations about appearance among peers, which was in turn related to body dissatisfaction (Clark and Tiggemann 2006). Social network sites may also impact body dissatisfaction indirectly through peer influence. If the use of social network sites increases peer appearance-related

feedback (H2a), and peer appearance-related feedback increases body dissatisfaction (H2b), then peer appearance-related feedback will mediate the effect of social network site use on body dissatisfaction among adolescents. We, therefore, hypothesized an indirect effect of social network site use on body dissatisfaction through peer appearance-related feedback (H2c).

The hypothesized relationships between social network site use, peer appearance-related feedback, and body dissatisfaction may differ in strength depending on adolescents' gender. The tripartite influence model emphasizes that adolescents' body dissatisfaction results from sociocultural channels exerting pressures to conform to unrealistic beauty ideals (Thompson et al. 1999b). Although sociocultural pressures to conform to appearance ideals influence both boys and girls (aged 12–16), research suggests that these pressures impact girls to a greater extent than boys (Jones et al. 2004). One experiment among adolescents aged 13–18 found that exposure to idealized appearance in mass media contributed to body dissatisfaction among girls but not among boys (Hargreaves and Tiggemann 2004). Furthermore, there is evidence that girls are generally subjected to such pressures to a greater extent than boys, at least among adolescents aged 12 to 16 (McCabe and Ricciardelli 2001). Research thus indicates that sociocultural influences on body image disproportionally affect girls.

Males and females may also differ in the degree of pressure to conform to appearance ideals that they experience on social network sites and the resulting impact of these pressures on body image. Young adults pay more attention to females' than males' physical appearance on social network sites (Seidman and Miller 2013). Furthermore, adult users evaluate females more strongly based on their physical appearance than males on social network sites (Manago et al. 2008). These gender differences may also occur among adolescents. According to the tripartite model (Thompson et al. 1999b), if social network sites exert greater pressures to look attractive on girls than on boys, the use of these social network sites will influence the body image of girls to a greater extent than the body image of boys. We, thus, hypothesized that social network site use will lead to body dissatisfaction more strongly among adolescent girls than boys (H3a).

One way in which social network sites may exert greater influence on girls' than boys' body image is that social network site use may increase the reception of appearance-related feedback to a greater extent for girls than for boys. In general, adolescent girls receive comments about their physical appearance more often than boys do, at least at ages 12–15 (McCabe et al. 2006). Furthermore, if people pay more attention to females' than males' physical appearance on social network sites (Seidman and Miller 2013) and girls are evaluated more strongly based on their appearance on these websites (Manago et al. 2008), the use of social network sites likely instigates more peer appearance-related feedback targeted at girls than peer appearance-related feedback targeted at boys. We, therefore, hypothesized that the effect of social network site use on peer appearance-related feedback would be stronger among adolescent girls than boys (H3b).

The effect of appearance-related feedback from peers on body image may also depend on the gender of the receiver. For example, in a study among adolescents aged 11–18, girls were more bothered by appearance-related feedback than boys, at least when it concerned weight-related teasing (Neumark-Sztainer et al. 2002). As a result, appearance-related feedback may be more detrimental to girls' than to boys' body image. In line with this notion, a meta-analysis of research among children, adolescents, and adults has shown that appearance-related feedback affects females' body image more negatively than males' body image (Menzel et al. 2010). We, therefore, hypothesized that the effect of peer appearance-related feedback on body dissatisfaction would be stronger among adolescent girls than boys (H3c).

Methods

Sample and Procedure

A two-wave panel survey was conducted by the Netherlands Youth Institute (Nederlands Jeugdinstituut) and Rutgers WPF (Dutch Expert Centre on Sexuality). In addition to the measures described below, the survey also included questions related to (sexual) media use, sexual attitudes and behaviors, and body image (as published in Nikken and de Graaf 2013; de Vries et al. 2014). The first wave was conducted in July through September 2008 and the second wave in December 2009. The survey was conducted among children of members of Intomart GfK, an online access panel that consists of 25,000 members across the Netherlands. Recruitment across the Netherlands improves generalizability in comparison with convenience samples. Coverage bias due to the use of an online panel was unlikely because Internet access was 98 % among people under 25 in the Netherlands (Centraal Bureau voor de Statistiek 2012).

In all, 3,160 Intomart GfK members who were parents of at least one child aged between 11 and 18 were contacted with a screening questionnaire and asked for permission to contact their children. Of these members 50.6 % responded, gave permission, and filled out the screening questionnaire completely. As a result, 1,600 adolescents were invited to participate in the first wave, of whom 1,294

(80.9 %) completed the questionnaire. For the second wave, adolescents who had completed the first questionnaire were asked, again via their parents, to complete a questionnaire similar to the first. In total, 604 adolescents (50.7 % female) completed all measures that were of interest for the current study in both waves. Retention rate was thus 54.2 %.

The age of participants in the final sample ranged between 11 and 18 ($M = 14.7$, $SD = 1.7$ at time 1; 50.7 % female). In this sample 20.1 % of the boys and 18.0 % of girls were aged 11–12, 33.9 % of boys and 41.2 % of girls were aged 13–14, 33.9 % of boys and 29.4 % of girls were aged 15–16, and 12.1 % of boys and 11.4 % of girls were aged 17–18. With regards to ethnicity, almost all parents (97.7 %) of the included adolescents reported having been born in the Netherlands. With respect to BMI, of the participants who reported their weight and height (13.1 % did not), 98.9 % reported a BMI under 30, 91.4 % of participants reported a BMI under 25, 52.3 % reported a BMI under 20, and 30.0 % a BMI under 18. Regarding parental monitoring of online behavior, only 2.5 % of parents reported knowing nothing about what their child does on the Internet, whereas 48.8 % reported knowing a lot about this and the remaining 48.7 % reported knowing a little about this. With respect to pubertal status, 73.2 % of the boys had experienced that their voice changed. Of the girls 81.0 % reported that they had experienced menarche. With respect to socioeconomic status, the highest category (A) was assigned to 11.9 % of participants. The second highest category (B1) was represented the most frequently with 41.2 % of participants assigned to this category. A further 21.9 % of participants were in category B2 and 23.3 % of participants were in category C. Only 1.7 % of participants were in the lowest socio-economic level (D).

There were no differences in terms of gender, $t(1292) = .082$, $p > .05$, or level of education, $t(1292) = -1.09$, $p > .05$ between adolescents who completed both waves and those who dropped out after the first wave. However, respondents who only completed one wave were 4 months older, on average, than respondents who completed both waves, $t(1292) = -3.32$, $p = .001$. The sample did not deviate from official Dutch population statistics in terms of gender, but participants were more likely to receive higher levels of education and to have parents born in the Netherlands than average for the Dutch population (Centraal Bureau voor de Statistiek 2012).

Measures

Social Network Site Use

Frequency of social network site use was assessed with the question: "How often did you visit Hyves.nl in the past 6 months?" The response options were 0 (*never*), 1 (*sometimes*), 2 (*regularly*), 3 (*often*), and 4 (*always*) ($M = 2.4$, $SD = 1.5$ at time 1; $M = 2.6$, $SD = 1.4$ at time 2). A single item was used as recommended for constructs that are concrete and singular (Bergkvist and Rossiter 2007). Although there were other social network sites on which some adolescents had a profile (e.g., MySpace), Hyves.nl was the dominant and most popular social network site at the time of the study (like Facebook is currently). Of adolescents aged 12–17, 75 % had a profile on the website (Mijn Kind Online 2009). The current survey also assessed the use of other social network sites that were around at the time of the survey. However, the use of these websites in this sample was negligible and, therefore, we only focused on popular social network site Hyves. Hyves.nl was comparable to Facebook in terms of its goal, set-up, and technological possibilities. Important for the current study is that on Hyves (like on Facebook, Instagram, Rate, and Bebo), posting personal photographs and comments on friends' profiles played a central role (Mijn Kind Online 2009).

Peer Appearance-Related Feedback

Peer appearance-related feedback was measured using a scale constructed specifically for the survey. This scale consisted of four items asking participants how often their friends (1) give them tips to get a more beautiful body, (2) give them criticism about their appearance or clothes, (3) give them tips to look sexy, and (4) tell them it is important to look good. The response options ranged from 0 (*never*) to 4 (*very often*). Factor analysis showed that the four items could be combined into a single factor that explained 62.6 % of the variance. The items were averaged to create a composite score. Cronbach's alpha was .79 at time 1 and .82 at time 2 ($M = 0.53$, $SD = 0.57$ at time 1; $M = 0.59$, $SD = 0.60$ at time 2).

Body Dissatisfaction

Body dissatisfaction was assessed using a version of the Dutch translation of the Body Areas Satisfaction Scale, a subscale of the Multidimensional Body-Self Relations Questionnaire (Cash 1994). This scale has been translated and successfully used among Dutch adult males and females (Woertman and van den Brink 2008). We used the formulations of the translation by Woertman and van den Brink (2008) and adapted it so that the specific body parts would be clearer for adolescents and could be used among both boys and girls. The scale consists of items that ask respondents how satisfied they are with eight different appearance attributes (face, hair, buttocks, stomach, breasts or chest, genitals, muscularity, and body weight). The

response options ranged from 0 (*very satisfied*) to 4 (*very dissatisfied*). Scores were averaged to create a composite score. Factor analysis revealed that all eight items loaded on a single factor that explained 49.1 % of the variance. Cronbach's alpha was .85 at time 1 and .84 at time 2 ($M = 1.46$, $SD = 0.65$ at time 1; $M = 1.45$, $SD = 0.65$ at time 2).

Additional Variables

In addition to the key variables, we also measured a number of additional variables at time 1 to provide more information on the sample. *BMI* was calculated as self-reported weight in kilograms divided by self-reported height in meters squared. BMI ranged from 13.59 to 36.73 ($M = 20.04$, $SD = 3.54$) in the current sample. *Parental monitoring of the adolescents' online behavior* was reported by one of the parents. This parent answered the question "How much do you know about what your child does on the Internet." This question could be answered with 0 (*I know nothing about this*), 1 (*I know a little about this*), or 2 (*I know a lot about this*) ($M = 1.46$, $SD = 0.55$). *Age* at time 1 was calculated from the self-reported birthdate and the date the survey was completed at time 1, and expressed in years ($M = 14.75$, $SD = 1.67$). *Pubertal status* was measured by asking the boys whether their voice had gotten lower and the girls whether they had experienced their first menstruation already. *Ethnicity* was assessed through parent-reported country of birth of this parent. *Socioeconomic status* of the family was measured using the Dutch gold standard used by Statistics Netherlands (Centraal Bureau voor de Statistiek 2012). This measure is based on the family breadwinner's level of education and current occupation. Based on the parental responses, participants were categorized into five categories ranging from low (D) to high (A).

Data Analysis

First, correlations were calculated between all measures at both time points for the sample as a whole and for boys and girls separately. Because the distributions of the scores on our key measures were skewed we calculated non-parametric correlations in Stata 12, namely Kendall's tau-a, and converted this value to an approximation of Pearson's r using Greiner's relation to aid interpretation, as recommended by Newson (2002). Subsequently, we tested the first hypothesis and the second set of hypotheses in four separate models (see Figs. 1, 2, 3 and 4) using structural equation modeling in SPSS, AMOS version 19. To test the direction of effects hypothesized in H1, H2a, and H2b, we used three cross-lagged models (Figs. 1, 2 and 3), testing both the hypothesized effect and the effect in the opposing

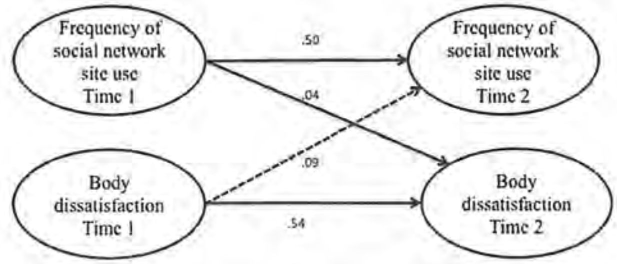

Fig. 1 Simplified illustration of AMOS model of relationships between social network site use and body dissatisfaction. *Numbers* indicate unstandardized regression coefficients for paths. *Dashed lines* indicate that the represented path was not statistically significant

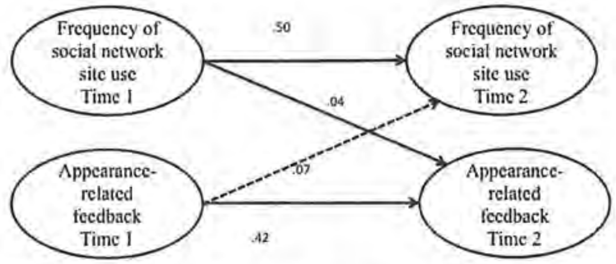

Fig. 2 Simplified illustration of AMOS model of relationships between social network site use and peer appearance-related feedback. *Numbers* indicate unstandardized regression coefficients for paths. *Dashed lines* indicate that the represented path was not statistically significant

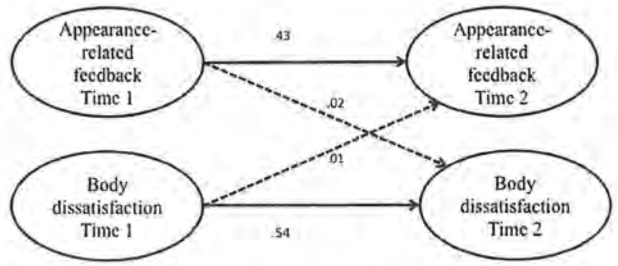

Fig. 3 Simplified illustration of AMOS model of relationships between peer appearance-related feedback and body dissatisfaction. *Numbers* indicate unstandardized regression coefficients for paths. *Dashed lines* indicate that the represented path was not statistically significant

direction. Then we modeled the hypothesized mediation effect postulated in H2c using the mediation model displayed in Fig. 4. In order to test the hypothesized moderation of gender specified in the third set of hypotheses, the models were subjected to multiple group analysis.

In the set-up of the models, we followed recommendations by Cole and Maxwell (2003). All analyses therefore included previous levels of the variables of interest. In this way, we controlled for past behavior, which increases the validity of the influence of the predictor variables at time 1 on the outcome variables at time 2 (Cudeck 1991; Gollob

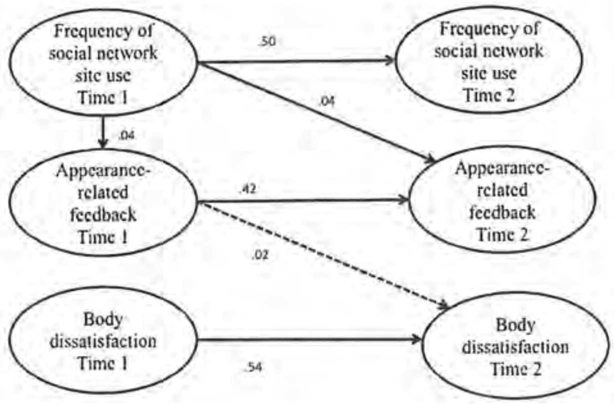

Fig. 4 Simplified illustration of AMOS model of the indirect effect between social network site use, peer appearance-related feedback and body dissatisfaction. *Numbers* indicate unstandardized regression coefficients for paths. *Dashed lines* indicate that the represented path was not statistically significant

and Reichardt 1991). In addition, all analyses controlled for gender, given the expected gender differences on the key variables. In the structural equation models, the eight items of the body dissatisfaction scale were combined into three parcels using the item-to-construct balanced procedure suggested by Little et al. (2002). Item parceling results in more parsimonious models and reduces the chance of double loadings and the influence of sampling error (Little et al. 2002). We included the single-item measure social network site use into the model as a manifest variable. The four items measuring peer appearance-related feedback were not subjected to item parceling, as there were not enough items to create three parcels, the recommended number in the item-to-construct balanced procedure (Little et al. 2002). Therefore, we included the four items as observed variables and loaded each item separately on the latent construct of peer appearance-related feedback.

The assumption of multivariate normality required for the traditional parametric tests was not met according to results of Shapiro–Wilk tests. In addition, Breusch-Pagan/Cook-Weisberg tests showed evidence of heteroscedasticity. To alleviate statistical problems due to violation of the assumption of normality we applied the bootstrap method to all models (1,000 bootstrap samples, $N = 604$ each) (Efron and Tibshirani 1993), and based our conclusions both on the bootstrap bias–corrected and accelerated 95 % confidence intervals as well as on the results of the parametric tests for the estimates. We only considered a hypothesis supported if the results of both tests were consistent. In addition, because parametric regression-based tests with heteroscedastic data can yield biased and inconsistent standard errors, resulting in Type 1 errors, we also conducted regression analyses with heteroscedasticity-consistent standard errors (hc3) in Stata 12, as recommended by Hayes and Cai (2007).

A number of variables may impact social network site use, peer appearance-related feedback, and/or body dissatisfaction: BMI, parental monitoring of the adolescent's online behavior, age, pubertal status, and socioeconomic status. These variables may thus act as third variables in the hypothesized models. As our models control for past behavior of each outcome, the models are expected to be fairly robust against third variable effects. However, as confounding effects may still occur, we also ran the models (Figs. 1, 2, 3 and 4) controlling for these factors. The control factors were entered in the model as manifest variables, covaried with the predictor variables, and paths representing the influence of the control factors on the outcome variables were drawn. The results are not included in the body of text of the results section, as we had not formulated specific hypotheses about the impact of these variables. Moreover, AMOS does not allow for analyses with missing cases and including the covariate BMI would result in a smaller and biased sample (525/604) because some adolescents did not report their height or weight. We provide information regarding these additional analyses in footnotes 1–4.

Results

Descriptive Statistics and Correlations

As shown in Table 1, girls visited social network sites more frequently, experienced peer appearance-related feedback more often, and were more dissatisfied with their bodies than boys. In addition to what is displayed in Table 1, it is interesting to note that, at time 1, 58.1 % of the boys and 79.1 % of the girls visited the social network site "regularly" to "always." At time 2, this was respectively 66.5 % and 87.3 %. In contrast, at time 1, 25.5 % (time 2: 19.8 %) of boys and 11.4 % (time 2: 5.9 %) of girls never used the social network site. Correlations between the measures are provided in Table 2.

Effect of Social Network Site Use on Body Dissatisfaction

The first hypothesis predicted that as adolescents use social network sites more frequently, their body dissatisfaction would increase. To test this hypothesis rigorously, we modeled the hypothesized influence of hypothesis 1, namely the effect of social network site use at time 1 on body dissatisfaction at time 2 in a structural equation model, and controlled for body dissatisfaction at time 1, as outlined in the "Methods" section. To test the alternative direction of effects, we also modeled the influence of body dissatisfaction at time 1 on social network site use at time

Table 1 Descriptive statistics

	Social network site use				Peer appearance-related feedback				Body dissatisfaction			
	Time 1		Time 2		Time 1		Time 2		Time 1		Time 2	
	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys
Mean	2.79***	2.03***	3.03***	2.19***	0.59**	0.47**	0.70***	0.47***	1.53**	1.38**	1.52**	1.37**
SD	1.42	1.56	1.17	1.46	0.60	0.53	0.63	0.54	0.65	0.69	0.67	0.62
Minimum	0	0	0	0	0	0	0	0	0	0	0	0
Maximum	4	4	4	4	3.25	3.25	3.25	3.75	4	4	4	4

Social network site use represents the frequency with which adolescents visit the social network site (0 = *never*, 4 = *always*). Peer appearance-related feedback represents how often peer appearance-related feedback is received from friends (0 = *never*, 4 = *very often*). Body dissatisfaction represents how satisfied respondents are with different appearance attributes (0 = *very satisfied*, 4 = *very dissatisfied*)

* $p < .05$ ** $p < .01$ *** $p < .001$ (two-tailed significance levels for differences in means between boys and girls)

Table 2 Zero-Order correlations

	Social network site (SNS) use		Peer appearance-Related feedback		Body dissatisfaction
	Time 1	Time 2	Time 1	Time 2	Time 1
SNS use					
Time 1	–				
Time 2	.58*** (.55/.53)	–			
Peer appearance-related feedback					
Time 1	.15*** (.20/.06)	.10* (.09/.06)	–		
Time 2	.18*** (.15/.12)	.14** (.09/.10)	.36*** (.31/.38)	–	
Body dissatisfaction					
Time 1	.05 (.01/.03)	.07 (.01/.05)	.07 (.07/.04)	.04 (.07/−.05)	–
Time 2	.11* (.13/.05)	.08* (.00/.10)	.02 (.02/.00)	.08 (.09/.02)	.57*** (.52/.60)

Correlations (Kendall's tau-a converted to an approximation of Pearson's r using Greiner's relation) for the total sample and for boys and girls (respectively) in brackets. Social network site (SNS) use represents the frequency with which adolescents visit the social network site (0 = *never*, 4 = *always*). Peer appearance-related feedback represents how often peer appearance-related feedback is received from friends (0 = *never*, 4 = *very often*). Body dissatisfaction represents how satisfied respondents are with different appearance attributes (0 = *very satisfied*, 4 = *very dissatisfied*)

* $p < .05$ ** $p < .01$ *** $p < .001$ (two-tailed, for total sample only)

2. The resulting model (see Fig. 1) achieved an excellent fit, $\chi^2(df = 17,\ N = 604) = 15.76$, $p = .54$, CFI = 1.00, RMSEA = .00 (90 % CI .00/.03). Frequency of social network site use positively and significantly predicted body dissatisfaction, $\beta = .10$, $B = .04$, $SE = .01$, $p = .008$. The bootstrap bias–corrected and accelerated 95 % confidence interval (Bt bca 95 % CI) ranged from .01 to .06. This confidence interval does not include zero, which indicates statistical significance. Body dissatisfaction at time 1 did not predict social network site use at time 2 in this model, $\beta = .04, B = .09, SE = .08, p = .271$ (Bt bca 95 % CI −.07/.27). Regression analyses with heteroscedasticity-consistent standard errors (hc3) also showed that social network site use at time 1 positively predicted body dissatisfaction at time 2, $B = .04$, $SE_{HC3} = .02$, $p = .008$ (95 % CI .01/.07). The findings thus supported H1, showing that social network site use predicts body dissatisfaction, but body dissatisfaction does not predict social network site use.[1]

[1] When we reran the model testing hypothesis 1 (Fig. 1) with control variables, the model again achieved good fit, $\chi^2(df = 37,\ N = 524) = 50.92$, $p = .063$, CFI = .99, RMSEA = .03 (90 % CI .00/.04). Frequency of social network site (SNS) use at time 1 again positively and significantly predicted body dissatisfaction at time 2, $\beta = .11$, $B = .04$, $SE = .02$, $p = .008$ (Bt bca 95 % CI .01/.08), again supporting hypothesis 1. Body dissatisfaction at time 1 again did not predict SNS use at time 2, $\beta = .03$, $B = .06$, $SE = .09$, $p = .491$ (Bt bca 95 % CI −.16/.25). Regarding the control variables, body dissatisfaction at time 2 was significantly predicted by higher BMI at time 1, $\beta = .09$, $B = .02$, $SE = .01$, $p = .035$ (Bt bca 95 % CI −.00/.03), but not by the other control variables. SNS use at time 2 was predicted significantly only by lower age, $\beta = -.10$, $B = -.08$, $SE = .03$, $p = .018$ (Bt bca 95 % CI −.14/−.01).

Effect of Social Network Site Use on Peer Appearance-Related Feedback

Hypothesis H2b predicted that as adolescents use social network sites more frequently, their received peer appearance-related feedback would increase. To test this hypothesis we modeled the figure shown in Fig. 2. This model achieved good fit, $\chi^2(df = 33, N = 604) = 72.01$, $p = .000$, CFI = .98, RMSEA = .04 (90 % CI .03/.06). Frequency of social network site use at time 1 positively and significantly predicted peer appearance-related feedback at time 2, $\beta = .10$, $B = .04$, $SE = .02$, $p = .016$ (Bt bca 95 % CI .00/.07). Peer appearance-feedback at time 1 did not predict social network site use at time 2 in this model, $\beta = .03$, $B = .07$, $SE = .09$, $p = .475$ (Bt bca 95 % CI −.11/.26). Regression analyses with heteroscedasticity-consistent standard errors (hc3) also revealed that social network site use at time 1 positively predicted appearance-related feedback from peers at time 2, $B = .04$, $SE_{HC3} = .02$, $p = .010$ (95 % CI .01/.07). The findings thus supported H2a, showing that social network site use predicts peer appearance-related feedback, but appearance-related feedback does not predict social network site use.[2]

Effect of Peer Appearance-Related Feedback on Body Dissatisfaction

Hypothesis H2b predicted that as adolescents receive peer appearance-related feedback more frequently, their body dissatisfaction would increase. To test this hypothesis we modeled the figure shown in Fig. 3. This model achieved good fit, $\chi^2(df = 74, N = 604) = 144.95$, $p = .000$, CFI = .98, RMSEA = .04 (90 % CI .03/.05). Frequency of peer appearance-related feedback at time 1 did not predict body dissatisfaction at time 2, $\beta = .02$, $B = .02$, $SE = .04$, $p = .706$ (Bt bca 95 % CI −.07/.12). Body dissatisfaction at time 1 also did not predict peer appearance-related feedback at time 2 in this model, $\beta = .01$, $B = .01$, $SE = .04$, $p = .768$ (Bt bca 95 % CI −.08/.14). In the regression analyses with heteroscedasticity-consistent standard errors (hc3), peer appearance-related feedback at time 1 also did not predict body dissatisfaction at time 2, $B = .00$, $SE_{HC3} = .04$, $p = .963$ (95 % CI −.08/.08). H2b was thus rejected.[3]

Mediation Model

The second set of hypotheses together stated that social network site use would predict increased peer appearance-related feedback (H2a), which in turn would predict increased body dissatisfaction (H2b), and therefore frequency of social network site use would indirectly lead to body dissatisfaction through peer appearance-related feedback (H2c). The second set of hypotheses was also tested in the AMOS model displayed in Fig. 4, in which the effects of social network site use (time 1) on peer appearance-related feedback (time 1 and time 2), and of peer appearance-related feedback (time 1) on body dissatisfaction (time 2) were modeled, in addition to the autoregressive paths. This model yielded a good fit, $\chi^2(df = 98, N = 604) = 180.88$, $p = .000$, CFI = .98, RMSEA = .04 (90 % CI .03/.05).

In line with H2a and the cross-lagged analysis (Fig. 2), the effect of social network site use at time 1 on peer appearance-related feedback at time 1 was positive and significant, $\beta = .11$, $B = .04$, $SE = .02$, $p = .023$ (Bt bca 95 % CI .00/.07) as was the effect of social network site use at time 1 on peer appearance-related feedback at time 2, $\beta = .10$, $B = .04$, $SE = .02$, $p = .022$ (Bt bca 95 % CI .00/.07). Contrasting H2b and in line with the cross-lagged analysis (Fig. 3), the effect of peer appearance-related feedback (time 1) on body dissatisfaction (time 2) was not significant, $\beta = .02$, $B = .02$, $SE = .04$, $p = .619$ (Bt bca 95 % CI −.06/.12). The indirect effect of social network site use (time 1) on body dissatisfaction (time 2) through peer appearance-related feedback (time 1) (H2c) was also not significant, $\beta = .00$, $B = .00$, $SE = .00$, $p = .483$ (Bt bca 95 % CI .00/.01). The indirect effect hypothesized under H2c was thus not supported.[4]

[2] When we reran the model testing hypothesis 2a (Figure 2) with control variables, the model again achieved good fit, $\chi^2(df = 70, N = 524) = 133.14$, $p = .000$, CFI = .97, RMSEA = .04 (90 % CI .03/.05). Frequency of social network site (SNS) use at time 1 again positively and significantly predicted peer appearance-related feedback at time 2, $\beta = .11$, $B = .04$, $SE = .02$, $p = .015$ (Bt bca 95 % CI .01/.08), again supporting hypothesis H2a. Peer appearance-feedback at time 1 again did not predict SNS use at time 2 in this model, $\beta = .02$, $B = .04$, $SE = .10$, $p = .666$ (Bt bca 95 % CI −.16/.22).

[3] When we reran the model testing hypothesis 2b (Figure 3) with control variables, the model again achieved good fit, $\chi^2(df = 124, N = 524) = 213.23$, $p = .000$, CFI = .98, RMSEA = .04 (90 % CI:.03/.05). Peer appearance-related feedback at time 1 again did not predict body dissatisfaction at time 2, $\beta = .04$, $B = .04$, $SE = .05$, $p = .342$ (Bt bca 95 % CI −.04/.16), again not supporting H2b. Body dissatisfaction at time 1 also again did not predict peer appearance-related feedback at time 2 in in this model, $\beta = .02$, $B = .02$, $SE = .05$, $p = .636$ (Bt bca 95 % CI −.09/.15). Body dissatisfaction at time 2 was again predicted by BMI, $\beta = .09$, $B = .02$, $SE = .01$, $p = .028$ (Bt bca 95 % CI .00/.03).

[4] The model in Figure 4 with added covariates also yielded a good fit, $\chi^2(df = 148, N = 524) = 248.23$, $p = .000$, CFI = .98, RMSEA = .04 (90 % CI .03/.04). The indirect effect of social network site use on body dissatisfaction (H2c) was again not significant, $\beta = .01$, $B = .00$, $SE = .00$, $p = .186$ (Bt bca 95 % CI .00/.01).

Moderation by Gender

The third set of hypotheses, predicting that the effects specified under H1 and H2a–b would be stronger among girls, was tested using multiple group analyses with gender as the grouping variable. To test H3a, predicting that the positive effect of social network site use on body dissatisfaction would be stronger among girls than boys, we first compared the model testing H1 (Fig. 1) with a model in which we constrained the path from social network site use (time 1) to body dissatisfaction (time 2). When the fits of the constrained and the unconstrained model differ significantly, the focal influence of the constrained path differs significantly between groups. This constrained model did not yield a significantly different fit than the unconstrained model, $\chi^2(1, N = 604) = 1.85$, $p = .174$, $TLI_{change} = .00$. This suggests that the effect of social network site use on body dissatisfaction was not moderated by gender, contrasting H3a.

We then compared the model testing H2a (Fig. 2) with a partly constrained model in order to test H3b, which noted that the positive effect of social network site use on peer appearance-related feedback would be stronger among girls than among boys. We, therefore, constrained the path from social network site use (time 1) to peer appearance-related feedback (time 2). This constrained model did not yield a significantly different fit than the unconstrained model, $\chi^2(1, N = 604) = .90$, $p = .343$, $TLI_{change} = .00$. This suggests that the effect of social network site use on peer appearance-related feedback was not moderated by gender. H3b was thus not supported.

To test H3c, which predicted that the positive effect of peer appearance-related feedback on body dissatisfaction would be stronger among girls, we constrained the path from peer appearance-related feedback (time 1) to body dissatisfaction (time 2) in Fig. 3. This constrained model did not have a significantly different fit than the unconstrained model, $\chi^2(1, N = 604) = 2.57$, $p = .109$, $TLI_{change} = .00$. Contrary to the predictions of H3c, the effect of peer appearance-related feedback on body dissatisfaction was thus not stronger among girls than among boys.

Discussion

The current study focuses on the impact of social network sites on adolescent boys' and girls' body image. The popularity of social network sites among adolescents (Lenhart and Madden 2007; Lenhart et al. 2010; SPOT 2012) and the centrality of physical appearance on these websites (Ringrose 2011; Siibak 2009) have led to concerns regarding their potential negative impact on adolescent body image (Tiggemann and Miller 2010; Tiggemann and Slater 2013). Previous research has established correlations between social network site use and body dissatisfaction among adolescent girls aged 13–18 (Tiggemann and Miller 2010; Tiggemann and Slater 2013). However, questions remained regarding the causal direction of this relationship, the mechanism underlying this relationship, and whether this relationship pertains to boys to the same extent as to girls.

The present study addressed these questions. Regarding the question of temporal direction, this longitudinal study shows that more frequent social network site use predicted increased body dissatisfaction among adolescents 18 months later but body dissatisfaction did not predict social network site use. With respect to the question about mechanisms underlying this relationship, we investigated peer appearance-related feedback as a potential mediator. We found that social network site use predicted more frequent reception of peer appearance-related feedback. However, peer appearance-related feedback did not predict body dissatisfaction. Appearance-related feedback, thus, did not mediate the effect of frequency of social network site use on body dissatisfaction. Regarding the question about the role of gender, boys were affected by social network site use in the same manner and to the same extent as girls. These findings have several theoretical and practical implications and offer useful insights for future research.

In terms of theoretical implications, the results of the current study shed new light on the nature of sociocultural influences on adolescent body image. The tripartite influence model (Thompson et al. 1999b) has considered parents, peers, and mass media as influences on body image. Our finding that social network site use augmented body dissatisfaction suggests that social network site use may be an additional sociocultural channel that influences adolescent body image. This influence may partly overlap with, or resemble, the influences from peers and mass media outlined in the tripartite model (Thompson et al. 1999b), but may also differ. Future research should further investigate the ways in which social network sites impact adolescent body image and focus on the extent to which this impact resembles, or differs from, the influences of mass media, parents, and peers.

The current study has explored a way in which social network sites may exert sociocultural influence on body image that is outlined in the tripartite model, namely through peer influence. As expected, more frequent use of social network sites predicted increased reception of appearance-related feedback from peers. However, we found that appearance-related feedback from peers did not predict body dissatisfaction over time. This finding is not in line with the tripartite model's notion that peer influence to conform to

appearance ideals leads to body dissatisfaction (Thompson et al. 1999b). One explanation for our findings may be that the impact of received peer appearance-related feedback on body dissatisfaction depends on the type and the valence of this feedback, at least among females aged 18 to 25 (Herbozo and Thompson, 2006). The current measure of peer appearance-related feedback did not distinguish different types of feedback. Receiving a mean comment about body weight from your best friend may have different effects on body image than a classmate providing you with tips to make your lips look fuller. Moreover, adolescents in the current sample on average experienced the type of peer influence assessed in the current study never to sometimes. As a result, the current study cannot assert definite conclusions about whether or not social network sites exert their pressures on body image through peer influence and future research is this area needed.

The lack of support for peer appearance-related feedback as an underlying mechanism as well as the low frequency of peer appearance-related feedback (Table 1) may also suggest that there are other, potentially more common, forms of sociocultural influence that mediate the effects of social network site use on body dissatisfaction. Studies should investigate whether and how the opportunities offered by new media to present the own body, to gain public feedback on one's appearance, and to scrutinize the bodies of others (Meier and Gray 2013; Ringrose 2011; Siibak 2009) affect the body image of its users in ways similar and different to face-to-face peer interactions and mass media exposure. As a result, the tripartite model (Thompson et al. 1999b) may be extended or adapted to incorporate ways in which body image is influenced by creating, sharing and responding to appearance-related content online.

An alternative explanation for the lack of support for the effect of peer appearance-related feedback on body dissatisfaction is that this effect may be stronger among, or confined to, a specific group of adolescents. Previous research has shown differential susceptibility regarding mass media influences on body image (e.g., Groesz et al. 2002; Stice et al. 2001). In the same way, peer appearance-related feedback as well as social network site use may also particularly influence the body image of certain vulnerable adolescents. In this respect, age and developmental characteristics could be relevant individual difference factors to consider (Bartlett et al. 2008; Groesz et al. 2002). The age range of the current study (11–18) was broad and sociocultural influences on body image may differ for adolescents at different ages and developmental stages (Bartlett et al. 2008; Groesz et al. 2002). Future research should thus identify potentially vulnerable groups in order to fully understand the impact of sociocultural influences, including peer appearance-related feedback and social network site use, on body image.

In addition to individual and developmental differences, cultural differences should also be taken into account when interpreting the current findings. For example, the finding that the relationships between social network site use, peer appearance-related feedback, and body dissatisfaction applied to the girls and boys to the same extent and in the same way may not generalize from our Dutch sample to adolescents in other countries. The Netherlands is considered to be a so-called feminine society, in which gender differences are less pronounced than in more masculine societies such as the US (Hofstede 1998). Therefore, a similar study in other countries may lead to different conclusions regarding the role of gender in body image.

Cultural context and other characteristics of our sample are also important to take into account with respect to other aspects of our findings. The adolescents in the current sample were more satisfied than dissatisfied with their bodies on average, with the mean level of body dissatisfaction being halfway between "not satisfied-not unsatisfied" and "quite satisfied." Moreover, the vast majority of adolescents were in the low or normal BMI range. In the current sample, 91 % of adolescents reported a BMI under 25 and 52 % reported a BMI under 20. Furthermore, on average the current sample never or sometimes received appearance-related feedback from friends. While this points to relatively healthy patterns in youth's relationships with their bodies among the adolescents in the current Dutch sample, the degree of body dissatisfaction and reception of peer appearance-related feedback may be more troublesome among adolescents in other countries or among certain potentially underrepresented Dutch subgroups. For example, it is documented that, among adult women, body dissatisfaction is lower in Western Europe than in North and South America (Swami et al. 2010). These cross-cultural differences may also apply to adolescents and present an important contextualization of our results. A replication of the current study's findings in other samples is thus needed to see if these findings generalize to other populations.

The current study has a number of shortcomings that future research can improve on. Future research in this area would benefit from experimental approaches in order to rigorously establish causality. The current study, with its two-wave panel design, can shed first light on the causal direction of relationships established in previous cross-sectional research. However, the current design does not have the same internal validity as an experimental design. Another shortcoming of our study refers to the investigation of hypothesized mediation. Although the current design offers a more thorough approach at establishing the temporal order of mediated effects than cross-sectional designs, a three-wave survey would have been preferable. A final limitation of the current study is the quality of the measurement of social

network site use. This measure consisted of only one item and measured the general use of only one social network site, which was very popular in the Netherlands when the study was conducted, but has declined in popularity since (Newcom Research and Consultancy 2012). As adolescents keep switching from one online platform to another, a recommendation for future research is to investigate the impact of activities that are not specific to one platform or to platforms at one moment in time.

In terms of practical implications, our study suggests that adolescents who report high levels of body dissatisfaction or who are at a greater risk for developing body image problems may benefit from interventions or guidelines to decrease the negative impact of social network site use on body image. Such interventions could be beneficial in the same way as some interventions seem effective at decreasing the negative effects of exposure to beauty ideals in the mass media on body image among adolescents aged 13–15 and young college-age women (Wilksch and Wade 2010; Yamamiya et al. 2005). Our finding that social network sites impact boys' body image to the same extent as girls' body image suggests that both boys and girls may benefit from such interventions. However, it is important to note that, in the current sample, girls did experience more peer appearance-related feedback and were more dissatisfied with their bodies than boys, although the differences were not extreme (see Table 1). In order to develop interventions and implement these effectively, we need to increase our understanding of how social network site use impacts body image, which specific social network site activities affect body image, among which adolescents this effect occurs most strongly, and under which conditions the effects come about.

Conclusion

This study offers a number of insights into the role that social network sites have come to play in adolescents' development and wellbeing. Previous research has shown that these increasingly popular websites (Lenhart et al. 2010; Lenhart and Madden 2007; SPOT 2012) impact adolescent development in several areas, such as adolescents' relationships and self-esteem (Gentile et al. 2012; Valkenburg et al. 2006). The current study has investigated whether and how social network sites also impact adolescent girls' and boys' body image—a crucial aspect of adolescent development and wellbeing (Markey 2010).

The current study contributes to the scarce knowledge about the relationships between social network site use and body image. Previous research has offered an initial indication that the use of social network sites is related to adolescent body image (Tiggemann and Miller 2010; Tiggemann and Slater 2013). In a number of ways, the current longitudinal study builds on these correlational studies among girls aged 13–18 (Tiggemann and Miller 2010; Tiggemann and Slater 2013). First, this study offers initial information about the causal direction of this association by showing that more frequent social network site use predicts increased body dissatisfaction over time. Second, the present study shows that social network site use predicts more frequent reception of peer appearance-related feedback. However, peer appearance-related feedback did not explain the effect of social network site use on body image because peer appearance-related feedback did not predict body dissatisfaction. Other mechanisms may be at play and/or only certain appearance-related feedback may lead to body dissatisfaction, only in certain situations or only among certain individuals. Third, this study shows that social network site use impacts the body image and reception of peer appearance-related feedback among boys to the same extent as among girls.

In this study, we offer a number of insights and suggestions that future research on adolescents' body image can build on. Specifically, more research is necessary to replicate the findings in other groups and countries, to assess which social network site activities impact body image and through which mechanisms, and to determine in which situations and among which adolescents the effects of social network site use on body image may be stronger or weaker. Nevertheless, the current study offers important evidence that social network site use poses a risk to adolescent boys' and girls' body image. Researchers, parents, and practitioners should aim to understand and try to counter these negative effects.

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Eating Behaviors

Norms and discriminative validity of the Eating Disorder Examination Questionnaire (EDE-Q)

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ABSTRACT

The first aim of this study was to provide norms for the Eating Disorder Examination Questionnaire (EDE-Q) in a diverse and large clinical sample of individuals with an eating disorder (ED), and a general population sample without an ED. Norms for individuals with obesity without an ED were also provided, as a more relevant comparison group for individuals with binge eating disorder. The second aim was to investigate the discriminative validity of the EDE-Q. A sample of females with an ED ($N = 935$), women from the general population without an ED ($N = 235$), and obese females without an ED ($N = 321$) completed the EDE-Q. Explorative factor analyses did not support the theorized four subscales of the EDE-Q. Norms for EDE-Q global scores were provided for each of the three samples. Within the ED sample, norms were provided separately for patients with different ED diagnoses. Receiver operating characteristic analyses showed the EDE-Q global score to be highly accurate in discriminating individuals with an ED from those without, and moderately accurate in discriminating individuals with binge eating disorder from those with obesity. The presented norms contribute to a more accurate interpretation of EDE-Q scores, providing an index of the severity level of ED psychopathology. Furthermore, these norms can be used to assess clinical significant change during treatment. In addition, this study demonstrates that the EDE-Q, when using its global score, is a valid instrument to assess levels of ED psychopathology.

1. Introduction

The Eating Disorder Examination (EDE) (Fairburn & Cooper, 1993) is a semi-structured interview that is widely considered the gold standard for the assessment of eating disorder (ED) psychopathology. However, the interview has certain disadvantages: it is relatively time-consuming (30–60 min), can only be administered to one person at a time, and interviewers need to be trained to administer it. Also, patients may find it embarrassing to admit potentially shameful behaviors, such as binge eating or purging, to an interviewer.

To address some of these disadvantages, a self-report version of the EDE, the Eating Disorder Examination Questionnaire (EDE-Q) (Fairburn & Beglin, 1994, 2008), has been developed. The EDE-Q is considered to be a viable alternative to the EDE and has been demonstrated to have acceptable to high internal consistency and test-retest reliability (Berg, Peterson, Frazier, & Crow, 2011).

Normative data are essential for appropriate interpretation of EDE-Q scores. Normative data can be obtained by administering a test to a representative sample, in order to establish norms, which are values that are representative of a group. Thus, normative data help to get a sense of the distribution of a certain characteristic (in this case, ED psychopathology) being assessed in a defined population. Normative data can furthermore be used in the measurement of clinical significant change (Jacobson & Truax, 1991), a concept that is becoming more and more important. For example, a certain treatment may be found to exert a statistically significant effect, however, it is important to determine whether this effect actually reflects meaningful, clinical significant change. That is, whether patients move to recovery and thus more healthy levels of functioning by the end of treatment. According to Jacobson and Truax (1991), the least arbitrary way to establish clinical significant change is to assess whether the levels of functioning after treatment places the individual statistically closer to the mean of the functional population than it does to the mean of the dysfunctional population.

EDE-Q scores and subsequent norms can vary among countries or subpopulations (Welch, Birgegård, Parling, & Ghaderi, 2011), because of cultural differences such as the prevalence of ED behaviors. Currently, normative data[1] on the EDE-Q are available for numerous general population samples (Carter, Stewart, & Fairburn, 2001; Lavender, De Young, & Anderson, 2010; Luce, Crowther, & Pole, 2008; Mond, Hay, Rodgers, & Owen, 2006; Øyvind, Reas, & Lask,

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[1] We refer to norms or normative data only when studies include at least means and percentile ranks of EDE-Q scores.

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2010; Villarroel, Penelo, Portell, & Raich, 2011; Welch et al., 2011). Yet, these norms are mainly based on samples of young (adolescent) women. Furthermore, to our knowledge, only two studies provide normative data for clinical population samples with an ED (Pennings & Wojciechowski, 2004; Welch et al., 2011). The clinical norms provided by Pennings and Wojciechowski (2004) do however not include norms for the frequency of core ED behaviors. Furthermore, these norms are solely based on a relatively small sample ($N=113$) of female patients with anorexia nervosa (AN), thus lacking norms for patients with an ED other than AN. Reports on the core ED behaviors provided by Welch et al. (2011), are limited by the lack of report on the medians of these ED behaviors, thereby missing some kind of normative information about the frequency of such behaviors.

Although the EDE-Q has demonstrated reliability (Berg et al., 2011), the validity of the EDE-Q, referring to the extent to which it measures what it is supposed to measure, has not yet been clearly established. One type of validity pertains discriminative validity (Streiner & Norman, 2012). If the EDE-Q actually measures ED psychopathology, then a group of individuals with an ED should score significantly higher than a group of individuals without an ED. Two studies suggested that the EDE-Q could accurately discriminate between individuals with an ED and those without (Mond, Hay, Rodgers, Owen, & Beumont, 2004; Mond et al., 2008). However, both studies were based on a small sample of cases ($N=13$ and $N=25$ respectively), and the cases included in the study by Mond et al. (2008) did not meet formal DSM-IV criteria (American Psychiatric Association, 1994) for an ED. Also, the samples of cases in both studies were relatively restricted: one included primarily variants of bulimia nervosa (BN) (Mond et al., 2008), and the other one included primarily individuals with (variants of) BN and binge eating disorder (BED) respectively (Mond et al., 2004).

The first aim of the present study was to provide norms for the EDE-Q in a diverse and large clinical sample of individuals with an ED (including individuals with AN, BN, BED, and eating disorder not otherwise specified (EDNOS)), and a general population sample without an ED. Norm scores for females with obesity without an ED will be provided as well, in order to provide a more relevant comparison group for the group of individuals with BED: a recent study found that individuals from a general population sample with obesity had twice as high EDE-Q global scores than individuals without obesity (Øyvind, Reas, & Rosenvinge, 2012). Prior to the establishment of normative data, the underlying factor structure of the EDE-Q was examined. Because, an important issue regarding the EDE-Q is that its four subscales were created on theoretical grounds and have never been empirically validated (Allen, Byrne, Lampard, Watson, & Fursland, 2011; Becker et al., 2010; Hilbert, de Zwaan, & Braehler, 2012; Hrabosky et al., 2008; Pennings & Wojciechowski, 2004; Peterson et al., 2007; Reas, Grilo, & Masheb, 2006). Based on the examination of the underlying factor structure, we determined whether it would be appropriate to make use of the theorized four subscales of the EDE-Q. This study subsequently reports both on the attitudinal features of ED psychopathology and the frequency of core ED behaviors.

The second aim was to reliably investigate the discriminative validity of the EDE-Q, by examining whether the EDE-Q could accurately discriminate between individuals with an ED and those without, and between individuals with BED and those with obesity without an ED respectively. This is an important test to assess whether the EDE-Q measures what it is supposed to measure, namely ED psychopathology.

2. Method

2.1. Sample

2.1.1. Sample of females seeking treatment for an eating disorder (ED sample)

All individuals seeking treatment (residential as well as outpatient) for their ED at our center, between 2006 and 2011, were assessed as part of our Routine Outcome Monitoring at the beginning of treatment. This sample consisted of 965 patients meeting the criteria for an ED according to the DSM-IV (American Psychiatric Association, 1994). Diagnoses were made by experienced clinicians specialized in ED, by means of a standardized semi-structured interview based on the DSM-IV criteria (American Psychiatric Association, 1994). After exclusion of males ($N=30$), a sample size of 935 was retained. Forty-one percent of the individuals met DSM-IV criteria (American Psychiatric Association, 1994) for AN ($N=382$), 19% for BN ($N=180$), 12% for BED ($N=112$) and 28% for EDNOS excluding BED ($N=261$).

2.1.2. General population sample

A total of 249 women were recruited through advertisements in Dutch university buildings and a university hospital ($N=60$), local magazines of these institutions ($N=20$), on the intranet of a mental health organization ($N=110$), and via other (personal) contacts ($N=59$). Fourteen women were excluded because they either reported suffering or having suffered from an ED, or having (had) severe eating problems that were indicative of an ED. A sample size of 235 was retained.

2.1.3. Sample of females seeking treatment for obesity (obese sample)

All individuals seeking treatment (outpatient only) for obesity ($N=414$) at our obesity outpatient program, between 2006 and 2010, were assessed as part of our Routine Outcome Monitoring at the beginning of treatment. All individuals had a Body Mass Index (BMI) of 30 or more and did not meet the criteria for an ED as assessed by a standardized semi-structured interview based on the DSM-IV criteria (American Psychiatric Association, 1994). After exclusion of males ($N=93$), a sample size of 321 was retained.

Socio-demographic characteristics of all samples can be found online (Supplementary Table 1). The total sample was predominantly Caucasian (92.9%). As indicated, all treatment-seeking individuals filled out the ED-Q as part of our Routine Outcome Monitoring. Since the Routine Outcome Monitoring is a standard procedure in the evaluation of the effectiveness of the treatment provided by the program, approval by a Medical Ethics Committee was not required. Data for the control group was collected as part of another study, which was approved by the ethics committee for mental health institutions in the Netherlands (METiGG).

2.2. Measures

2.2.1. Eating Disorder Examination Questionnaire (EDE-Q)

The original 36-item version of the EDE-Q (Fairburn & Beglin, 1994) was used. The main difference between this version and the more recent 28-item version (Fairburn & Beglin, 2008), is that the former includes questions about diuretic misuse and subjective binge eating episodes, whereas the latter does not. Both versions include the same 22 items assessing the core attitudinal features of ED psychopathology, with the newer version containing some minor adjustments in the phrasing of some items. The 22 items together comprise four subscales, assessing restraint, shape concerns, weight concerns and eating concerns over the previous 28 days. These items are answered on a 7-point Likert scale ranging from 0, 'not one day', to 6, 'every day'. Items within each subscale can be summed and averaged to provide subscale scores. A global score can be calculated by summing and averaging the subscale scores. Higher scores are indicative of higher ED psychopathology. Another fourteen questions assess to frequency of core ED behaviors, being how many times the behavior occurred over the previous 28 days. The present study used a Dutch translation of the EDE-Q, which was made with permission of the developers of the questionnaire (Fairburn & Beglin, 1994).

2.3. Statistical analyses

The internal consistency reliability of the EDE-Q was measured with Cronbach's α coefficients. An exploratory factor analysis (principal component analysis) using a direct oblimin rotation was conducted to examine the underlying factor structure of the 22 attitudinal items of the EDE-Q. We chose not to impose a predefined factor structure on the outcome (e.g. confirmatory factor analysis), given that previous studies did not show a consistent picture regarding the underlying factor structure of the EDE-Q. Only factors with eigenvalues over one were retained.

A multivariate analysis of variance (MANOVA) and follow-up univariate analyses of variance (ANOVAs) were conducted to test for differences in EDE-Q scores and behavioral measures among patients with different ED diagnoses. Norms were provided using descriptive analyses.

To investigate the discriminative validity of the EDE-Q, receiver operating characteristic (ROC) analyses were conducted. For each of these analyses, we calculated an area under the curve (AUC). An AUC is a reflection of how well the test discriminates between two groups of individuals. According to Swets (1988), an AUC of 0.9 or greater has high accuracy, while 0.7-0.9 indicates moderate accuracy, 0.5-0.7 low accuracy, and 0.5 a chance result.

Cases with missing data were excluded from the analyses. All statistical analyses were performed in SPSS version 19.

3. Results

3.1. Internal consistency reliability

Internal consistencies were calculated using the whole sample ($N=1491$). Cronbach's α coefficients were high: global score, $\alpha=.95$; restraint, $\alpha=.85$; eating concern, $\alpha=.81$; weight concern, $\alpha=.83$; shape concern, $\alpha=.91$.

3.2. Factor structure

The underlying factor structure of the EDE-Q was examined using the ED sample ($N=935$). The explorative factor analysis produced four factors explaining 61.92% of the variance. However, the produced four factors did not provide support for the theorized four subscales (for more information see Supplementary Table 2, which can be found online). The first factor included three items of the theorized shape concern and one item of the weight concern subscale. The second factor contained all five items of the theorized restraint subscale, as well as two items of the theorized eating concern subscale, and another item which has been theorized to belong both in the weight- and shape concern subscale. The third included two items of the theorized eating concern subscale. The fourth factor contained items of the theorized shape concern (four items), weight concern (three items), and eating concern subscale (one item). In addition, we examined the correlations between items belonging to the same theorized subscale, to correlations between items belonging to different theorized subscales, and found these to be fairly similar. This suggests that the theorized four subscales are in fact not separable sub dimensions, but that all items together tap one general underlying dimension (e.g. ED psychopathology).

Given that the theorized four factor structure of the EDE-Q was not supported, we considered it inappropriate to make use of the EDE-Q subscales in the subsequent analyses. We therefore analyzed data with respect to the EDE-Q global score only. We calculated a new global score by summing and averaging all individual items, so that each items had equal weight and the global score would thus no longer be based on the non-supported subscales. Based on the whole sample, the mean of the new EDE-Q global score was 0.13 points higher than the mean of the EDE-Q global score calculated in the original way: a small and clinical insignificant difference (Cohen's $d=-0.08$).

3.3. Norms

In the ED sample, a MANOVA revealed significant differences in EDE-Q global scores and behavioral measures across patients with different ED diagnoses ($F(24, 2680.48)=12.28$, $p<.001$). Follow-up ANOVAs revealed significant differences with respect to the EDE-Q global score ($F(3, 931)=14.11$, $p<.001$), objective binge eating ($F(3, 931)=18.48$, $p<.001$), laxative misuse ($F(3, 931)=8.26$, $p<.001$), excessive exercising ($F(3, 931)=18.07$, $p<.001$), self-induced vomiting ($F(3, 931)=36.63$, $p<.001$), and fasting ($F(3, 931)=19.58$, $p<.001$). Non-significant differences were found for diuretic misuse ($F(3, 931)=19.58$, *ns*) and subjective binge eating ($F(3, 931)=2.30$, *ns*).

Since most of the above mentioned variables showed significant differences among patients with different ED diagnoses, norm scores were not only provided for the ED sample as a whole, but separately for patients with different ED diagnoses as well. Table 1 presents means, standard deviations and percentile ranks of the EDE-Q global score for the different samples. For each of the samples, the proportion of individuals that reported engaging in ED behaviors, at any occurrence or at regular basis, is shown in Table 2. For most of these ED

Table 1
Means, standard deviations and percentile ranks for the global score of the Eating Disorder Examination Questionnaire (EDE-Q) for a group of women from the general population, a sample of females seeking treatment for an eating disorder and a sample of females seeking treatment for obesity.

	General population	Eating disorder population					Obese population
	($N=235$)	Total ED ($N=935$)	AN ($N=382$)	BN ($N=180$)	BED ($N=112$)	EDNOS ($N=261$)	($N=321$)
Mean (SD)	0.93 (0.86)	4.02 (1.28)	4.17 (1.30)	4.34 (1.04)	3.46 (0.98)	3.83 (1.40)	2.75 (0.97)
Percentile rank							
5	0.04	1.41	1.50	2.46	1.98	1.09	.95
10	0.09	2.14	2.18	2.91	2.32	1.55	1.41
15	0.18	2.61	2.61	3.27	2.45	1.96	1.73
20	0.23	2.91	2.95	3.55	2.59	2.70	1.92
30	0.32	3.50	3.73	4.06	2.95	3.25	2.32
40	0.45	3.95	4.18	4.41	3.23	3.68	2.59
50	0.64	4.36	4.55	4.57	3.50	4.32	2.86
60	0.89	4.64	4.86	4.85	3.77	4.50	3.05
70	1.15	4.91	5.09	5.00	3.91	4.77	3.27
80	1.63	5.18	5.32	5.18	4.23	5.09	3.55
85	1.87	5.32	5.41	5.27	4.45	5.18	3.73
90	2.29	5.41	5.50	5.40	4.73	5.35	4.00
95	2.69	5.55	5.64	5.55	5.24	5.50	4.27
100	4.59	6.00	6.00	6.00	5.68	6.00	5.23

ED = eating disorder; AN = anorexia nervosa; BN = bulimia nervosa; BED = binge eating disorder; EDNOS = eating disorder not otherwise specified.

Table 2
Proportion of a group of women in the general population, a sample of females seeking treatment for an eating disorder and a sample of females seeking treatment for obesity, who reported engaging in disordered eating behaviors over the past 28 days, as measured by the Eating Disorder Examination Questionnaire (EDE-Q).

Key behavior	Any occurrence (%)						Regular occurrence (%)					
	General population	Eating disorder population				Obese population	General population	Eating disorder population				Obese Population
	(N=235)	AN (N=382)	BN (N=180)	BED (N=112)	EDNOS (N=261)	(N=321)		AN	BN	EDNOS	BED	
Fasting	3.4	50.3	45.0	11.6	42.1	8.7	0.0	25.7	15.6	16.5	3.6	1.6
Objective binge episodes	3.9	33.5	81.7	85.7	42.9	38.0	0.4	28.5	77.2	35.6	75.9	28.9
Subjective binge episodes	10.2	55.0	71.7	53.6	61.7	28.7	3.8	47.4	65.0	52.9	48.2	20.9
Self-induced vomiting	1.3	32.8	79.3	0.0	34.5	2.8	0.0	28.0	70.6	26.1	0.0	1.2
Laxative misuse	0.8	25.7	27.8	0.0	22.2	2.8	0.0	22.8	22.8	19.2	0.0	2.8
Diuretic misuse	0.0	1.8	2.2	0.0	0.8	0.3	0.0	1.6	2.2	0.8	0.0	0.0
Excessive exercising	38.5	44.0	38.9	0.0	49.8	15.6	0.0	29.1	17.2	19.2	0.0	2.5

AN = anorexia nervosa; BN = bulimia nervosa; BED = binge eating disorder; EDNOS = eating disorder not otherwise specified.
Regular occurrence is defined as ≥4 occurrences over the past 28 days, with the exception of fasting (≥13 days) and excessive exercising (≥20 days).

behaviors, medians were found to be 0, which means that 50% of the individuals in these samples scored 0. Below, we will report on the medians of the behavioral measures which were not equal to 0, in order to provide some more information on the distribution of these characteristics in the defined population. With respect to objective binge eating episodes, a median of 16 was found in the BN sample, and a median of 10 was found in the BED sample. This means, for example, that 50% of the individuals in the BN sample reported less than 16 binge eating episodes in the past 28 days. Regarding self-induced vomiting, a median of 12.5 was found in the BN sample. For fasting, 50% of the individuals in the AN sample reported fasting on one to five days in the past 28 days. The medians of subjective binge eating episodes were found to be 3 in the AN sample, 8.5 in the BN sample, and 2.5 in the BED sample.

3.4. *Discriminative validity of the EDE-Q*

First, a ROC analysis was conducted to investigate the ability of the EDE-Q global score in discriminating between individuals with an ED and those without. The ROC analysis demonstrated an AUC of .96 (95% CI = .95–.97), meaning that the EDE-Q global score could highly accurately (Swets, 1988) discriminate between individuals with an ED and those without. It means that there is 96% likelihood that the EDE-Q global score of a randomly chosen individual in the ED sample will be higher than a randomly chosen individual in the general population sample. In discriminating between individuals with BED and those with obesity, the EDE-Q global score was found to be moderately accurate (AUC = .72, 95% CI = .67–.77).

4. Discussion

To our knowledge, this is the first study to provide norms for the Eating Disorder Examination Questionnaire (EDE-Q) of three (age) diverse and large samples of females, namely a clinical sample with an eating disorder (ED), including patients with AN, BN, BED and EDNOS, as well as a general population sample without an ED, and an obese sample without an ED. This is furthermore the first study to reliably examine the discriminative validity of the EDE-Q.

The current study did not provide support for the theorized four factor structure (Fairburn & Beglin, 1994) of the EDE-Q, a finding consistent with other studies (Allen et al., 2011; Becker et al., 2010; Pennings & Wojciechowski, 2004; Peterson et al., 2007). It is remarkable that no study to date has empirically supported the theorized four subscales of the EDE-Q, especially since numerous other studies have based their norms or analyses (at least partly) on these non-supported subscales (Carter et al., 2001; Lavender et al., 2010; Luce et al., 2008; Mond et al., 2006; Villarroel et al., 2011; Welch et al., 2011). Future studies should carefully consider whether to make use of the theorized subscales and subsequent scoring methods of the EDE-Q. Given the lack of support for the theorized four subscales of the EDE-Q, we calculated a new global score by summing and averaging all individual items, so that all items possessed equal weight and were thus no longer based on the non-supported subscales. Nevertheless, the mean of the new EDE-Q global score is comparable to the EDE-Q global score calculated in the original way.

Norms for the EDE-Q global score were established for both the attitudinal features of ED pathology and the frequency of core ED behaviors, for a clinical sample of females seeking treatment for their ED, a sample of women from the general population without an ED, and a sample of females seeking treatment for obesity without an ED. These norms can now be used in (clinical) practice, not only when it comes to interpreting EDE-Q scores, thereby providing an index of the severity level of ED psychopathology, but also in the measurement of clinical significance change during treatment. In addition, this study demonstrated the discriminative validity of the EDE-Q global score: it was highly accurate in discriminating between individuals with an ED and those without, and moderately accurate in discriminating between individuals with BED and those with obesity without an ED. This implicates that the EDE-Q, when using its global score, is a valid instrument to assess one's general level of ED psychopathology.

The EDE-Q global score and frequencies of core ED behaviors from our general population sample appear somewhat lower than those reported for numerous other general population samples (Carter et al., 2001; Luce et al., 2008; Mond et al., 2006; Villarroel et al., 2011; Welch et al., 2011), with the exception of excessive exercising, which shows quite comparable reports. The general population differences in EDE-Q scores could reflect cross-cultural differences in the prevalence of ED behaviors. Differences in EDE-Q scores could also reflect differences in age, given that the mean age in our general population sample was higher than those of other general population samples, which mainly included young (adolescent) women (Carter et al., 2001; Luce et al., 2008; Mond et al., 2006; Villarroel et al., 2011; Welch et al., 2011). An explanation might be that EDE-Q global scores are inversely related to age (Mond et al., 2006; Øyvind et al., 2012).

When comparing our results from the ED sample to a Swedish ED sample (Welch et al., 2011), results with respect to the EDE-Q global scores are quite similar, but results regarding the frequencies of core ED behaviors show some discrepancies. Amongst all of the four ED samples, our samples reported less occurrences of fasting and diuretic misuse, and somewhat less occurrences of self-induced vomiting as compared to the Swedish samples. Conversely, our ED samples generally reported more occurrences of laxative misuse. These differences may reflect cross-cultural differences in the expression of ED symptoms, in interpretation of the items, and/or in the availability of diuretics and

laxatives. Also, differences in age might be an explanation for the discrepancies in the frequencies of core ED behaviors, given that our ED sample had a higher mean age than the Swedish ED sample.

Results of this study should be considered in the context of a few limitations. Norms should be interpreted with caution, given that levels of ED psychopathology can vary across samples of different countries and regions, and even among samples within the same population. Furthermore, the female sample of individuals with an ED was recruited from a single clinical center specialized in ED which treats the most severely ill patients in the Netherlands. Forty-four percent of our ED sample received residential treatment, and particularly among patients with AN, the majority (80%) received residential treatment. Also, our different samples were not matched for age. We cannot rule out the possibility that differences in age somehow influenced EDE-Q scores. Although our samples showed significant differences in educational levels, we consider it unlikely that there is a causal relationship between educational achievement and eating pathology. The differences in educational levels could possibly be explained by the fact that our treatment-seeking sample did not have time to start or finish their education because of their relatively younger age, or that they were simply unable to because of their illness. A further limitation of this study is that it was restricted to females, and it is unknown whether the results of this study would generalize to males. Furthermore, no reliable diagnostic tool such as a standardized clinical interview was used to assess ED psychopathology in the sample of females from the general population. However, we did ask these females whether they were suffering or having suffered from an ED, or having (had) severe eating problems that were indicative of an ED, and excluded these individuals subsequently. A study by Keski-Rahkonen et al. (2006) suggested simple screening questions to be just as good and reliable as other established, but longer and more time consuming instruments.

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Contributors

All authors contributed to the design of the study. Author A conducted literature searches and provided an overview. Authors B and C were involved in data collection. Authors A and C conducted statistical analyses. All authors contributed to, and were involved in writing the manuscript.

Conflict of interest

All authors declare that they have no conflicts of interest.

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12

2024 International Conference on Informatics, Multimedia, Cyber and Information System (ICIMCIS)

The Impact of Social Media Filters on Body Perception and Psychological Well-Being in Adolescent Girls : Systematic Literature Review

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Abstract— **The increasing prevalence of mental health issues among adolescents can be linked to the pervasive influence of online social media in contemporary life. This comprehensive literature review examines the impact of social media filters on adolescent girls' body image and mental well-being. It focuses on studies published in peer-reviewed journals from 2019 to 2024. Employing a rigorous search methodology, forty relevant articles were identified and analyzed. To ensure the quality and pertinence of the research, the selection process involved formulating specific research questions, utilizing targeted keywords, and applying stringent inclusion and exclusion criteria. The review underscores the widespread use of social media filters and their potential to induce negative mental health outcomes, such as anxiety, depression, and diminished self-esteem in adolescent girls. Furthermore, these filters may distort body image perceptions and exacerbate body dissatisfaction. The findings emphasize the urgent need for further research and interventions aimed at mitigating the adverse effects of social media on adolescents' perceptions of their bodies and mental health.**

Keywords—Social media, Body perception, Body image, Psychological well-being, Social media filters, Adolescent

I. INTRODUCTION

The impact of social media usage on both positive and negative outcomes has been well-documented. While technology facilitates connectivity across geographical barriers, it can also have detrimental effects on mental health and overall well-being. This comprehensive review aims to examine the complex relationship between social media filters and adolescent girls' psychological health and body image perception. In particular, the analysis will explore how the idealized imagery and filters prevalent on social media platforms influence users' self-perceptions, body image, and mental health. Additionally, it will investigate the role of social comparison, the rising trend of cosmetic surgery, and the links between social media usage, mental distress, anxiety, and depression. By synthesizing the findings of 40 studies, this review contributes to a deeper understanding of social media's effects on the mental health and body image of teenage girls.

The studies reviewed offer significant new insights into how social media affects mental health and body image. Research by Engeln et al. [1], Gurtala and Fardouly [2], and Tiggemann and Anderberg [3] specifically examined the relationship between social media usage and body image. Engeln et al. [1] found that college-aged women experienced a decline in body satisfaction after just seven minutes of Instagram use. Similarly, Gurtala and Fardouly [2] concluded that exposure to idealized images and videos negatively impacted young women's body image. Tiggemann and Anderberg [3] compared "Instagram vs. reality" images and observed that viewing realistic images led to less body dissatisfaction than viewing idealized ones. These studies underscore the negative effects of social media on body image concerns.

Moreover, the link between social media use and mental health was explored by Keles et al. [4], Huang [5], and Smith et al. [6]. Keles et al. [4] discovered that adolescents who frequently use social media report higher levels of anxiety, depression, and psychological distress. Huang [5] investigated the detrimental effects of problematic social media usage on well-being, finding a negative correlation between excessive usage and life satisfaction. According to Smith et al. [6], a one-week social media detox significantly improved participants' overall mental health, well-being, and body image. These studies collectively demonstrate the adverse effects of social media usage on mental health outcomes.

In addition, the increasing normalization of cosmetic procedures was examined by Hermans et al. [7] and Van Oosten et al. [8]. Hermans et al. [7] found that highly visual social media platforms contributed to the normalization of cosmetic treatments, both actively and passively. Van Oosten et al. [8] noted that social comparison and the need for self-validation encouraged appearance-related concerns, which indirectly influenced the selection of visually-oriented social media platforms. These findings highlight the role social media plays in shaping perceptions and acceptance of cosmetic surgery.

While the majority of participants in this study are adolescent females, it is essential to acknowledge that social media usage influences individuals across all age groups and genders. Research focusing specifically on the impact of social media on male adolescents is scarce; the limited studies conducted in this domain include the work of Jarman et al. [9] and Vuong et al. [10]. Future investigations should aim to include a more diverse range of samples to gain a comprehensive understanding of how social media affects body image and mental health across various demographic groups.

II. METHODOLOGIES

A. Current Study

This comprehensive literature review examined data concerning the influence of social media filters on adolescent females' perceptions of their bodies and mental health. The

objective was to inform policy and practice while also guiding future research in this domain.

B. Methodology

In line with the stated goals, this study sought to answer the following questions:

1. How do adolescent females' perceptions of their bodies and their levels of body dissatisfaction relate to the use of social media filters?
2. What is the association between the prevalence of mental health issues, such as anxiety, depression, and low self-esteem, among adolescent females and their use of social media filters?
3. What interventions can effectively mitigate the negative effects of social media filters on adolescent females' body perceptions and psychological well-being?

C. Search Strategy

Articles published on the Impact of Social Media on Body To identify relevant literature, articles examining the impact of social media on body image, body dissatisfaction, and body perception in adolescent females were sourced from the Scopus Q1 and Q2 databases. The *Publish or Perish* software, which retrieves and analyzes academic citations, was utilized to assist in the search. This software gathers data from various academic sources and provides metrics such as citation counts, h-indexes, and article totals.

The researcher entered relevant keywords into the tool, including "impact of social media on body image," "body dissatisfaction," "social media," and "body image in adolescent females." These search terms were carefully selected based on a preliminary review of the literature addressing the influence of social media on body dissatisfaction and body image among adolescents. The retrieved articles were then filtered based on inclusion and exclusion criteria to identify the most relevant studies. The search parameters are detailed in Table 1, and the resulting articles, including title, authors, journal, year of publication, and citation count, are presented in Table 2.

TABLE I. DATABASE RESEARCH RESTRICTION

Category	Specification
Language	English
Timeline	2019-2024
Database	Scopus, Science Direct, PubMed, PsycINFO
Subject area	Psychology, Computer Science
Literature type	Article, Review
Keyword Search	"Impact of Social Media on Body Image", "Body Dissatisfaction", "Social Media", AND "Body Image in Adolescent Females"

Fig. 1. Publish or Perish Result

Following the acquisition of search results, the investigator sorted the articles according to pertinent study-related keywords, abstracts, and titles. 200 articles were found by searching for them using the predefined criteria. After these articles' titles and abstracts were examined, 120 pertinent articles were left after more filtering. After obtaining the 120 articles, the full articles were read in order to perform an additional screening. In the end, 40 publications that satisfied the requirements were chosen and examined for this research. The Clarivate, H-, and Scopus indices were used to select the articles. While mjl.clarivate.com (Web of Science) was used to check the Clarivate Index, scimagojr.com was used to check the Scopus Index and H-Index. Table 2 displays the findings from these assessments.

TABLE II. JOURNALS LIST

Journals	Qty	Index (Scopus)	H-Index	Clarivate
International Journal of Adolescence and Youth	1	Q1	36	√
Body Image	20	Q1	108	√
Preventive Medicine Reports	1	Q1	53	√
Comprehensive Psychiatry	1	Q1	122	√
Heliyon	1	Q1	88	√
Computers in Human Behavior	5	Q1	251	√
Clinical Epidemiology and Global Health	1	Q1	32	√
Internet Interventions	1	Q1	52	√
Appetite	1	Q1	178	√
Journal of Psychosomatic Research	1	Q1	176	√
Acta Psychologica	1	Q1	112	√
BMC Psychiatry	1	Q1	137	√
Children	1	Q2	50	√
International Journal of	1	Q1	82	√

Journals	Qty	Index (Scopus)	H-Index	Clarivate
Social Psychiatry				
International Journal of Environmental Research and Public Health	1	Q2	198	√
BMC Women's Health	1	Q2	64	√
Current Opinion in Psychology	1	Q1	89	√
Journal of Health Psychology	1	Q2	105	√

D. Research Mapping

In total, 40 articles were included in this review. As previously mentioned, we only accept articles from officially recognized publications. The keyword mapping of articles using the VOSViewer and Publish or Perish tools is displayed in Fig 2.

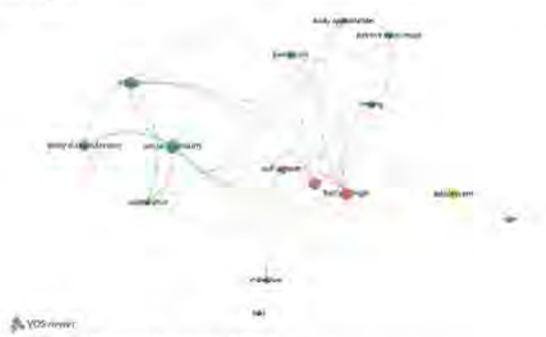

Fig. 2. Viewer Mapping Model

The relationship between items or keywords was mapped using co-occurrence mapping, also referred to as a semantic network in VOSviewer. All terms are viewed as analytical units in co-occurrence mapping, with the entire computation process serving as support. A distribution of the articles used over time is shown in Fig. 3. From 2019 to 2024, as can be observed, is the year interval.

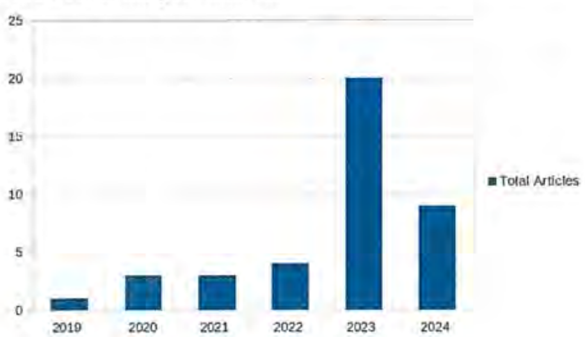

Fig. 3. Distribution of the Articles

III. RESULT

A. Description of Studies

After conducting a method-based analysis, a content-based review was performed to synthesize findings from 40 selected studies relevant to the research questions (RQ). The effects of this synthesis are presented in this phase. Notably, twenty of the analyzed studies were sourced from the *Body Image* journal, which focuses on how adolescents and young adults interact with social media. The evaluation aimed to identify potential relationships between teenage social media use and mental health, with particular emphasis on how social media filters influence perceptions of one's body and contribute to dissatisfaction. Furthermore, the review sought to explore the correlation between the use of social media filters and the prevalence of mental health conditions such as depression, anxiety, and low self-esteem among adolescent girls. Collectively, these studies provided valuable insights into how excessive use of social media filters can exacerbate body dissatisfaction, distort body image, and lead to various negative psychological outcomes.

B. Analysis of Results

Research indicates that social media usage may adversely affect both mental and physical health, particularly among adolescent girls. Social media exposure is frequently discussed in relation to its impact on body image, as filters often distort positive body perceptions, leading to dissatisfaction. Additionally, increased usage is associated with higher levels of anxiety, depression, and distress. Social media also normalizes cosmetic procedures, with platforms increasingly contributing to their acceptance. Moreover, social comparison is prevalent, as appearance-consciousness and self-esteem influence the preference for visually-driven platforms.

C. Filters Distoring Body Image and Leading to Dissatisfaction

The studies revealed that social media filters can distort body image and lead to dissatisfaction. Studies by Engeln et al. [1], Tiggemann and Anderberg [3], and Van Oosten et al. [8] found that exposure to idealized images and videos on social media platforms like Instagram and Facebook negatively impacted body image and increased dissatisfaction. Additionally, Li et al. [11] and Vuong et al. [10] discovered that higher social media usage, particularly Instagram and Snapchat, was associated with increased body dissatisfaction. Furthermore, Smith et al. [6] and Hooper et al. [12] found that a break from social media improved mental health and reduced body dissatisfaction.

D. The Influence on Mental Health, with Higher Usage Correlating to Increased Depression, Anxiety, and Distress

Numerous studies have demonstrated that social media filters distort body image and contribute to dissatisfaction. Exposure to idealized images and videos on platforms such as Facebook and Instagram has been shown to negatively affect body image and increase discontent, as reported by Engeln et al. [1], Tiggemann and Anderberg [3], and Van Oosten et al. [8]. Furthermore, research by Li et al. [11] and Vuong et al. [10] found that "frequent use of social media, particularly Instagram and Snapchat, was associated with higher levels of body dissatisfaction". Smith et al. [6] and Hooper et al. [12] also observed that "taking a break from

social media led to improved mental well-being and reduced body dissatisfaction".

E. Normalization of Cosmetic Procedures, with Frequent Exposure to Visual Platforms Increasing Acceptance

The increasing normalization of cosmetic procedures has been closely tied to the prominence of social media platforms that heavily feature visual content. According to studies by Hermans et al. [7] and Hollett and Challis [13], "frequent engagement with visually dominant platforms such as Instagram and TikTok contributes significantly to the growing acceptance of cosmetic treatments". Hermans et al. [7] further found that "both passive and active participation in these platforms heightened individuals' intentions to pursue cosmetic procedures, suggesting that appearance-focused content has a direct positive influence on attitudes towards such treatments". Moreover, these studies explored how social media shapes individuals' body perceptions and self-worth. Notably, women who spent more time viewing clothing images online tended to place greater emphasis on their appearance, often leading to increased concerns about their physical image, as highlighted by Hollett and Challis [13].

F. Role of Social Comparison, with Appearance-Consciousness and Self-Esteem Influencing the Choice of Visually-Focused Platforms

The use of social media, especially on visually focused platforms like Instagram and Snapchat, is influenced by concerns over beauty and social comparison. Studies by Gurtala and Fardouly [2], Engeln et al. [1], Van Oosten et al. [8], and Tiggemann and Anderberg [3] demonstrated that "exposure to idealized images and videos on these platforms intensifies social comparison and negatively impacts body image". Further research by Li et al. [11] and Vuong et al. [10] found that "higher social media usage was linked to increased body dissatisfaction, particularly among individuals who internalized narrow or muscular body ideals". Jarman et al. [9] and Keles et al. [4] also discovered that "excessive social media use correlates with poorer mental health outcomes, including elevated levels of psychological distress, anxiety, and depression". These findings illustrate the significant effects of social media on body image and mental well-being, especially among adolescent girls.

IV. DISCUSSION

The use of social media filters plays a critical role in shaping adolescent girls' perceptions of their bodies and psychological health. Among the forty studies reviewed, the most frequently measured outcomes were body dissatisfaction and body image concerns, particularly in relation to the influence of social media filters and the portrayal of idealized images. Several studies also investigated the connection between social media use and mental health, with a focus on psychological distress, anxiety, depression, and social comparison. The findings indicated that social media usage contributed to negative psychological outcomes, including decreased body satisfaction and increased negative affect. Additionally, the studies examined other factors such as cognitive biases, self-compassion, social comparison, orthorexia nervosa, and the normalization of cosmetic procedures.

From informatics point of view AI and algorithms are used by social media companies to spread filtered photos that inflate notions of beauty. Body dissatisfaction results from these filters' distortion of body perception, particularly in adolescent girls. Theory of Reasoned Action (TRA) states that users' attitudes and beliefs are shaped by continuous exposure to idealized images, which leads them to look for ways to conform to these ideals, such as applying filters or thinking about making cosmetic adjustments. Solution development can benefit from an informatics perspective on data analysis regarding filter usage and effects. Encouraging the use of more diverse and realistic imagery on social media platforms could potentially mitigate its negative effects on mental health and body image.

Numerous studies, including those by Gurtala and Fardouly [2], Tiggemann and Anderberg [3], and Engeln et al. [1], "have specifically examined the effects of social media use on body dissatisfaction and body image". According to research by Engeln et al. [1], "college-aged women who used Instagram for just seven minutes reported lower satisfaction with their bodies". Similarly, Gurtala and Fardouly [2] found that "exposure to appearance-focused content, whether in the form of photos or videos, had a negative impact on young women's body image". Tiggemann and Anderberg [3], in their comparison of "Instagram vs. reality" images, discovered that "viewing real-life photos and "Instagram vs. reality" pictures reduced body dissatisfaction more effectively than viewing idealized, flawless images".

In addition to body image concerns, studies by Smith et al. [6], Huang [5], and Keles et al. [4] "explored the connection between social media use and mental health". Keles et al. [4] found that "adolescents who frequently used social media experienced higher levels of anxiety, depression, and psychological distress". Similarly, Huang [5] "identified an inverse relationship between problematic social media use and well-being, including reduced life satisfaction". Smith et al. [6] observed that "a one-week reduction in social media use resulted in improved mental health, well-being, and body image".

V. CONSLUSION

The substantial negative impact of social media on young women's body image and mental health is further underscored in the systematic review, "The Impact of Social Media Filters on Body Perception and Psychological Well-Being in Adolescent Girls." The review highlights how the use of filters and the proliferation of idealized images on platforms such as Instagram and Snapchat contribute to distorted body perceptions and increased body dissatisfaction among adolescent girls. While viewing "Instagram vs. reality" and authentic images provided some mitigating effects, research by Engeln et al. [1] and Tiggemann and Anderberg [3] demonstrated that "even brief exposure to idealized imagery significantly affected body satisfaction". This suggests that while social media can negatively impact body image, promoting realistic and unfiltered images could help counteract these effects and foster a more positive body perception among adolescent girls.

Moreover, extensive evidence points to a strong link between social media use and mental health challenges, including anxiety, depression, and diminished well-being. Keles et al. [4] and Huang [5] "established clear associations between increased social media usage and mental distress, particularly among adolescent girls who are more susceptible to internalizing beauty standards and engaging in social comparison". Smith et al. [6] "provided further support for the benefits of reducing social media consumption, finding

that a one-week social media fast improved mental health and well-being". These findings underscore the urgent need for interventions aimed at mitigating the adverse psychological effects of social media filters and promoting more responsible usage behaviors.

Some interventions may help mitigate the harmful effects of social media filters on body image and mental health, particularly among adolescent girls. Educational programs that foster critical media literacy and raise awareness of the unrealistic nature of social media filters can empower young women to navigate these platforms more healthily. Additionally, promoting content that features diverse body types and authentic representations of beauty can help normalize realistic body perspectives and reduce the pressure to conform to idealized standards. Complementary to strategies aimed at curbing excessive social media use, mental health support addressing the root causes of body dissatisfaction and low self-esteem is essential in safeguarding the psychological well-being of adolescent users. The analysis concludes that developing comprehensive approaches to enhance the mental health of teenage girls in the digital age must account for the sociocultural influence of social media and its impact on body image.

A. Limitation

While the research under evaluation provided valuable insights, it is crucial to recognize their limitations. Fewer studies specifically addressed male adolescents, with a larger focus placed on female participants. Additionally, the majority of these studies were conducted in Western countries, limiting the generalizability of the findings to other cultural contexts. Furthermore, much of the research concentrated on the impact of social media on mental health and body image, whereas other potential effects, such as social connections or knowledge acquisition, were not explored as extensively.

The methodologies of the studies also varied; some employed surveys or interviews, while others used experimental approaches. Due to small sample sizes, the findings from certain studies may not be as broadly applicable. Additionally, although several social media platforms were analyzed, with Instagram, Facebook, and TikTok being the most commonly studied, the effects of emerging platforms may have been overlooked.

Despite these limitations, the studies offer valuable information regarding the influence of social media on adolescent girls' body image and mental health. To address these constraints and further investigate the complex relationship between adolescent development and social media use, more research is needed.

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